GIS Mapping of Retail Food Access to Assess Risks of (Chronic and Acute) Illness in Populations of Different Socioeconomic Status

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Characteristics of the built environment, including availability and type of retail food outlets, vary with area poverty. This affects consumption patterns of area residents and may, in turn, affect both local incidence of obesity and rates of food borne illness. This research utilizes a unique approach to analyze retail food access and food safety risk. Geographic information systems (GIS) were used to plot retail food listings, from two databases, and foodservice critical health code violations (CHV) over poverty in Philadelphia Co., Pennsylvania.

Retail listings were purchased from Dun and Bradstreet (D&B) and identified using inspection records from the Philadelphia Health Department (PDPH). Addresses were geocoded to census tracts (N=368). Tracts were classified into quintiles using Census Bureau poverty data. GIS overlay analysis was used to group locations within tracts.

To examine degree of retail food access produced by both data sources, Chi-square statistic was utilized to test interaction between poverty and store type. Using either database (D&B, N=4,263; PHD, N=5,847), a significant interaction was found between poverty and the distribution of food markets, indicating that rates of all grocery stores, including corner markets, were highest in high poverty areas. Further analysis revealed that high poverty areas contained both lower percentages of chain markets and supermarkets compared to low poverty areas. Though fast food was more prevalent in high poverty areas versus low, the interaction between poverty and the distribution of fast-food and full service restaurants was only significant using PDPH but not D&B. Significant differences in distances to convenience and grocery stores were similar between datasets. However, D&B failed to show significant differences in travel distance to supermarkets across poverty groups, while lowest poverty groups (highest income) were

significantly different from other groups using PDPH. Significant differences in distance to fast food and full service restaurants between poverty groups were similar using both datasets. However, the relative literature-established direction of the relationship between poverty and proximity to fast food restaurants was conserved using PDPH but not D&B.

To examine distribution of CHV, PDPH inspection records from 2005 to 2008 for all public foodservice locations (N=10,859) were analyzed. Less than half (46.5%) of facilities had an average of zero CHV. The average rate of CHV for all foodservice facilities was 0.765 per inspection. Rates of CHV across poverty groups were significantly greater in the lowest poverty (highest income) group at 0.93 (0.04) compared to other groups. Average days between inspection was also significantly greater in the two lowest poverty (highest income) groups compared to higher poverty groups.

These results confirm an association of increased access to chain food markets for low poverty areas and increased access to corner markets/groceries for high poverty areas in Philadelphia. Furthermore, results suggest that data source can affect the assessment of food environments and subsequent interpretation of degree of impact on residents' health. These results also indicate an association of higher rates of violations and longer periods between inspections with lowest poverty rates. This study demonstrates the use of GIS technology to assess food safety risks and the novel comparison of two data sources to assess community food access.

CHAPTER ONE: BACKGROUND AND LITERATURE SURVEY

1.1 Effect of poverty on general health

Poverty has been dubbed the *world's deadliest disease*.[1] Many economic factors contribute to the health of the individual. In general, a higher income may allow for better health, affording opportunities like better medical care, housing in lower crime neighborhoods, disposable funds and/or time for leisure-time physical activity.[2] Additionally, diet may play a major role in the health disparities observed across socioeconomic lines.

Disparities in health outcomes exist between residents of high and low income areas. The socioeconomic status of an area can impact health outcomes ranging from birth weight to mortality rate. In addition to factors at the level of the individual, the SES of an area is associated with infant birth weight, such that less advantaged areas are associated with low birth weight.[3] Longitudinal studies using national data have found an association between higher incomes and lower rates of mortality.[4-6] Krieger et al found an association between "fewer economic resources" and "higher mortality rates" after plotting various-cause mortality and cancer incidence data against socioeconomic status.[7] This finding held true independent of race, ethnicity and gender.[7]

1.2 Effect of poverty on chronic disease: obesity

Obesity in the United States has been on the rise over the past three decades.[8-9] In adults age 20-74 years, the prevalence of obesity, defined by a body mass index (BMI) of ≥ 30 kg/m^2, has risen from 15% in 1976-1980 (NHANESII) to 32.2% in 2004.[9] Obesity has many negative health implications. Overweight and obesity confer higher risk of hypertension, diabetes, coronary heart disease[10] and even death from both cardiovascular disease and obesity-related cancer.[11] In addition to detriments to personal health, obesity has increased the financial burden on the healthcare system. Finkelstein et al. (2003) estimate that obese Medicare (Medicaid) recipients cost $1,486 ($864) more per year than such recipients of normal weight.[12]

Research has elucidated the relationship between SES and incidence of chronic illnesses, specifically overweight and obesity (and associated comorbidities).[2, 13] Paeratakul et al (2002) utilized self-reported height, weight and sociodemographic measures, as a part of the CSFII 1994-96. In the study, low income was defined as 130% or less than federal poverty guidelines for household size and income, while high income was greater than 130% of guidelines. In this nationally representative, cross-sectional sample of more than 9600 people, the authors found that the prevalence of obesity was significantly higher in individuals with low income than those with high income.[14]

Obesity is caused by many factors. However, at its most basic level, weight gain results from a caloric imbalance: more energy is consumed than is expended. Many factors affect this weight regulation equation on both the consumption and the expenditure sides. These factors may be classified as genetic/biological or environmental. Environmental factors may include the types of foods available in an individual's surroundings and the degree to which one's surroundings promotes physical activity. Though it is the complex interaction between biology and environment and their effects on diet and exercise which determines overall energy balance,[15] the focus of this review is on the impact of the local food environment on the diet and health of the individual.

1.2.1 Factors of the built environment that impact diet choice and health

The physical characteristics of an environment, if positive, can influence the development and maintenance of healthy living.[16] The environmental characteristics affect diet choice via factors such as retail accessibility and cost of food.

- **Accessibility.** Though the thought and behavior processes behind food-choice are highly complex,[17] what we eat is largely made up of what exists in our surroundings. Research has shown that the types of available food outlets and type of foods available for purchase in an individual's immediate surrounding have been found to affect the food choice of the individual.[13, 16, 18-19] In this respect, an individual's health and weight status may be affected by characteristics of the local food environment, namely, food outlet type and availability. The impact of the availability of three types of outlets (supermarkets, grocery stores and fast-food restaurants) is discussed below.

- **Cost of food.** Cost is an important factor in the decision to process a food.[17] The cost of a food, in turn, is affected by its macronutrient composition, among other factors.

Nutrient density is a term commonly used to describe the relative quantity of micronutrients per kilocalorie. The density of nutrients in a food, however, is generally inversely proportional to the density of calories, or energy density (calories per gram weight). Energy density (ED) is a term used to describe the relative concentration of kilocalories per unit weight in a food. Water and fat are the two food components that contribute the most to the ED value of a food, given their extreme energy values (water 0 kcal/g; fat 9 kcal/g). Of the two, however, the effect of water is the most profound as the lower the water content, the higher the ED.[20] Diets low in energy density are typically high in fruits and vegetables and are, thus, associated with higher quality diets[21-22] and lower BMIs.[23]

The ED of a food is also generally inversely related to energy cost, defined as dollar per calorie.[2] If a family is on a limited budget, it may be more cost effective to meet energy needs of the family using energy dense, shelf-stable foods (containing added sugars and fats) than energy-dilute foods (including fruits and vegetables), which are typically highly perishable. A study of the diets of French adults concluded that economic constraints may indeed influence the type of groceries purchased. In order to keep the cost of the diet low, the foods purchased must be higher ED.[24] This will likely lead to weight gain because diets high in ED are typically high in total calories[23, 25] and high in percent of calories from fat and sugar.[26-27]

Recent research has confirmed the lower cost of energy dense diets compared to energy-dilute diets. In a large (N=837), observational study, Darmon and colleagues collected 6-month food frequency information from participants in France. Their results not only confirmed previous findings that ED is negatively correlated with fruit and vegetable consumption, but also showed an inverse relationship between dietary ED and diet cost.[27]

In addition to the relatively higher cost of fruits and vegetables compared to fats and sweets, those with lower incomes may be paying more for food in general. MacDonald and Nelson[28] performed a market-based analysis of the average price of grocery orders, with identical contents, in ten major metropolitan areas. Supermarkets within urban and suburban areas of the 10 locales were randomly selected from a trade magazine's listings, providing 322 stores total. A "price index" was determined for each store, based on the average price of selected items from the store, compared to the average price for those items across all stores. They found that foods in higher poverty areas (i.e. $\geq$ 20% of population living below poverty line) cost, on average, 2% more than non-poverty areas. This difference was statistically significant.

As early as 1973, it was shown that the cost per unit weight of a food is affected by the size of store. That is, an item purchased at an independent grocer will cost more than the same item purchased from a chain grocer.[29] The degree of access to these stores varies by SES, as discussed below.

1.2.2 Retail types, respective foods sold and effects on diet and weight

- **Supermarkets and groceries**. Supermarkets, or large-scale food stores, may be part of a chain, and typically offer both a wide variety of a full range of foods[30] and more heart-healthy, nutrient-dense foods when compared to small-scale, independent grocers (i.e., grocery stores).[19, 31] Supermarkets also typically offer lower general food prices than grocery stores in urban environments,[32] though there may not be a great difference in prices in rural areas.[30] Grocery stores may also offer a relatively wide range of food items. However, they are typically smaller in size than supermarkets, and may thus offer a limited variety of items.[30]

Availability of particular food outlets have been shown to impact the dietary choices, and thus, weight status, of area residents. Cheadle et al[33] found significant positive associations between the availability of nutritious food and "healthfulness of individual diets" as measured by self report. Generally speaking, the greater the number of supermarkets in an area, the more fruits and vegetables are consumed by residents.[18] Supermarket patrons have also been found to consume more fruits and vegetables than those shopping at independent groceries.[34] Additionally, the availability of large scale food stores has been associated with a decreased prevalence of overweight and obesity[35] and with lower BMI of residents in the vicinity.[36]

- **Fast food.** Fast-food restaurants can be defined as self-service or carry-out eating places where convenience food may be purchased.[37-39] Generally, patrons select, order and pay for food before consumption.[40] These locations only sell prepared, ready-to-eat foods and the foods are typically lower in nutrient density and higher in calories than what is offered at either supermarkets or grocery stores.

In an analysis of data from the CSFII, Binkley and colleagues[41] examined the importance of the source of the food with the individuals BMI. The survey utilized a nationally representative sample of over 16,000 participants. After controlling for confounding factors, participants who ate at a fast food restaurant on the two non-consecutive days of the survey were heavier than those who did not.[41] Pereira et al (2005) found a similar result from a prospective, longitudinal (15y) study (N=5115). The study produced a 74% final retention rate. There were no differences between drop outs and participants for baseline BMI or frequency of fast food visits. Upon follow up, the authors found that those who maintained a higher frequency of consumption of fast food gain an additional 4.5kg over the study, compared to those who maintained a low consumption frequency.[39]

In addition to an increased likelihood of weight gain, those who consume fast food are also more likely to have poorer quality diets than those who do not. Using data from the CSFII, analyses confirmed that the diets containing fast food also contained more calories, fat, added sugar, and carbohydrate, while containing less dairy, fruits and non-starchy vegetables.[42-43] These findings are consistent with other studies which reveal a decrease in nutrient density of diets containing fast-food,[44] indicating a poorer quality diet.

- **Full service restaurants.** Establishments considered to be full service restaurants, by definition, are eateries where patrons are typically served ordered food and pay for their food after eating.[45] In a study examining the relationship between individual weight data and restaurant availability indicated by the Economic Census, Mehta and Chang found that a greater density of full service restaurants in an area was associated with lower BMIs of residents, and vice versa.[46]

1.2.3 Food access varies according to socioeconomic status

The research discussed above highlights the potential impact of the local food environment on weight status and diet quality. In areas where there are more supermarkets than grocery stores, residents tend to consume more healthful diets and exhibit lower weights and BMIs. In areas where there are a large number of fast food restaurants, residents tend to have poor quality diets and carry excess weight. As one might expect, there is a great deal of variability in the composition of an area's food environment. One factor contributing to the variation is the socioeconomic status (SES) of the area. This relationship is discussed below.

Overweight and obesity in populations may be linked to the degree of access to healthier, low energy density food choices, including fresh produce. This unequal access to healthier food may promote the observed gradient in weight-related health.[13, 47]

Those of higher SES are found to have reduced access to less nutritious (i.e., fast-food) food outlets, compared to those of lower SES.[48-49] Conversely, those of lower SES are more likely to have reduced access to healthy food options (i.e., large-scale food stores), compared to those of higher SES.[47] Accessibility may be affected by both outlet availability and available transportation.

Compared to residents of HSES areas, it has been found that residents of LSES areas have less access to large scale, chain stores (supermarkets).[13, 50-51] Those of LSES areas, however, have greater access to smaller, independently operated food markets and fast-food/take-out restaurants, compared to those of HSES.[13, 47, 50, 52] In a 2002 study by Morland et al, conducted in selected areas of Mississippi, North Carolina, Maryland and Minnesota, census tracts were classified based on neighborhood wealth. Upon survey of each census tract, greater numbers of all food service places were found in HSES areas compared to LSES areas. Supermarkets were found to be four-times more prevalent in HSES areas than areas of LSES composition.[50] Data from grass roots organizations such as The Food Trust in Philadelphia also lend support to the association between impoverished communities and reduced access to supermarkets.[53]

The number of fast-food establishments has been found to be associated with the SES of an area. In a study by Block et al (2004), a greater number of fast food establishments were found in areas of predominantly lower SES than areas of predominantly higher SES.[54] Similarly, Cummings et al (2005) found a significant positive association between degree of neighborhood deprivation and the number of McDonald's restaurants in the UK.[55] A similar finding was reported by Powell and colleagues (2007) where, using national data from the 2000 Census, lower income areas were found to have the highest number of fast food restaurants, when compared to higher income areas.[49]

Pearce and colleagues found a negative linear relationship between area deprivation (i.e. poverty) and the distance traveled to a fast food restaurant in New Zealand. The relationship is similar, albeit positive, for distance to healthier options (i.e. supermarkets).[56] Reidpath et al found a similar trend, with areas of lower income earners being exposed to 2.5 times the fast-food restaurants as areas of higher median income in Australia.[57] In general, the lower the SES of an area, the greater the access to fast-food restaurants.

1.2.4 Use of datasets to quantify food access

The research studies described above quantify area food access. However, the source of retail listings often differs across studies. Commonly used databases are often commercially available, pay-for-access services such as Info USA, Trade Dimensions, and Dun and Bradstreet, though some are publically available lists obtained via municipal offices. There is limited data on the degree of completeness and/or limitations of these types of databases. Databases can be verified through visits to individual addresses, known as ground truthing. However, it is common for databases to contain thousands of records, making the ground truthing process prohibitively costly. Some studies suggest that commercial lists may be an appropriate proxy for direct observation. Paquet et al (2008) employed ground truthing to validate commercially available and internet listings for retail food establishments in 12 census tracts in Montreal. The authors found that the commercial list, provided by Tamec Inc. Business 411, was superior to the internet list in agreement with ground truthing results. However, the commercial list contained a greater number of establishments no longer in business, indicating that the commercial list may not have been truly up to date.[58] Similarly, in a study comparing agreement between commercially available listings and ground truthing in Chicago, Bader et al (2010) suggests that either commercially available source or ground observations are reasonably appropriate methodologies. Their study also suggests that commercially available lists may generally under represent all existing establishments, regardless of area socioeconomic status.[59] Cummins et al (2009) utilized establishment listings available on the public register in the UK. Ground-truthing revealed "reasonable" agreement with the publically available dataset where 1 in 9 listed establishments could not be confirmed through field observation.[60]

Comparisons between databases yields mixed results, however. Wang et al (2006) compared two government datasets, including records from city licensing and the State Board of Equalization, to 3 commercial listings, including telephone business directory, Trade Dimensions and Dun and Bradstreet, across census tracts in 4 Californian cities to assess agreement of databases. Their analysis included only listings from the State Board of Equalization and the telephone business directory as the other databases lacked information on smaller groceries. They found that while the government listing contained 36 records not listed in the telephone book, the telephone directory contained 260 records not listed in the government dataset. The authors suggest that researchers use caution when applying historical data to examine the local food environment.[61]

Given the health and policy implications of associating neighborhoods with low supermarket- and high fast food density, the aim of the current study is to compare food access as determined by 2 different data sets; a publically available dataset from the municipality, Philadelphia Department of Public Health, and a commercially available dataset, Dun and Bradstreet.

1.3 Effect of poverty on food borne illness risk

A number of health outcomes are associated with the availability of economic resources, but the relationship between acute incidence of foodborne illness and income is not well understood. Though it is estimated that over 76 million cases of illness and about 5,000 deaths occur annually in the U.S. as a result of foodborne pathogens,[62] the proportion of illness experienced by low income groups compared to high income groups is still not clear.

1.3.1 Incidence statistics are influenced by variations in care seeking behavior

Rates of reported illness are affected by many factors. Incidence rates are calculated from care-seeking efforts and confirmed by stool sample. According to CDC surveillance networks, almost 18,000 cases of foodborne illness across 10 states were confirmed by laboratory tests in 2007 and the confirmed incidence rate is not different from previous years.[63] Yet, in a study surveying more than 31,000 people over a two year period, 5% reported experiencing diarrhea in the month prior to the survey.[64] Only 20% of ill respondents sought medical care and only 19% of those who sought care provided a stool sample. Results from a study following 9,776 participants in the UK between 1993 and 1995 revealed estimates that for every one case presented to physicians, there are about 5 non-reported cases in the community. [65] Wheeler et al (1999) further estimate that, in the UK, there are 136 community cases for every one case reported to laboratory surveillance.[65] Confirmed cases, therefore, represent a fraction of actual cases.

Furthermore, studies have confirmed differences in care-seeking behavior based on a number of factors including illness severity,[66] duration and presence of other (non-respiratory) symptoms.[64] Research also suggests a difference in care seeking behavior and/or related FBI rates across populations of varying socioeconomic demographics, discussed below.

1.3.2 Relationship between SES and incidence of food borne illness

Though there is a long standing, clear association between poverty and incidence of foodborne illness in third world nations, [67-69] the relationship between incidence of foodborne illness and socioeconomic status in developed countries appears to be very complex. Additionally, study design may affect calculated rates of disease incidence. Aside from a limited number of prospective studies, the majority of relevant studies are retrospective in design. The use of retrospective self-report is thought to produce overestimates of actual disease incidence.[65]

- **Low SES linked with high FBI incidence.** Some studies have demonstrated an association between lack of economic resources and incidence of foodborne illness. In the UK, incidence of infectious intestinal disease, as measured by hospital admission rates, has been shown to be positively associated with degree of "social deprivation."[70] "Low social class" was also one of factors directly associated with salmonella infection in a study of Italian children.[71] Additionally, certain symptoms of food borne illness (nausea, vomiting, and constipation, but not heartburn or diarrhea) were associated with low socioeconomic status (LSES) in a survey of upper and lower gastrointestinal symptoms in 9000 Australians.[72] Most recently, evidence presented by Chang et al (2009) indicates that incidence rates of salmonellosis and shigellosis are positively and independently associated with high poverty areas.[73]

Furthermore, unpublished data from this laboratory suggests that the relative risk of reporting bacterial infection from foodborne pathogens increases from 1.7 to 1.97 when percent below poverty increases from $\geq$ 15% of individuals below poverty to $\geq$ 60% of individuals below poverty.

- **No clear relationship between SES and incidence of FBI.** One study has shown that no clear association exists between SES and incidence of foodborne illness. In a retrospective, cross-sectional, one-time telephone survey of Ontario residents (N=3496), self-reported incidence of acute gastrointestinal illness was examined across demographics. Incidence was only marginally associated with income (p=0.07) but not associated with education level at all.[74] The authors purposefully left the definition of gastrointestinal illness vague to enhance detection, though this may have confounded findings ('food poisoning' was the second most commonly reported reason for experienced gastrointestinal illness behind 'flu/virus').[74]

- **High SES linked with high incidence of FBI.** A few studies have found that high SES groups are more likely to contract and/or seek care for a foodborne pathogen or gastrointestinal illness, though the exact mechanism is a subject of debate. Retrospective studies using self-report and recall have linked high education to high incidence of infection. Using 52,840 completed telephone surveys to assess past incidence of acute diarrheal illness in residents of FoodNet sites, Jones et al (2007) found that the rate reported by adult respondents with more than a high school degree was greater than the rate reported by respondents with less than a high school education.[75] Furthermore, laboratory confirmed bacterial illness rates have been associated with measures of SES. Younus et al (2007) found a dose-dependent relationship between education and laboratory confirmed cases of salmonellosis such that decreasing years of education was associated with a decrease in infection incidence rates reported between 1997 and 2006 in Michigan.[76] Additionally, increased SES was positively associated with increased incidence of Campylobacter infections in Canada.[77]

Though studies investigating the association between SES and laboratory confirmed foodborne illness provide the strongest evidence for the link between high SES and FBI, findings from a prospective study also supports the association between SES and incidence of infectious gastrointestinal illness. The results from a nationwide prospective cohort study (N=4860) in the

Netherlands provide additional evidence that incidence of infectious gastroenteritis incidence increases with education level.[78] It should be noted that there was a slight overrepresentation of highly educated participants in study population compared to the general population, but correction revealed a similar result.

- **Over- and under-reporting of gastric illness by social class.** Explanations for increased care seeking rates among either higher or lower SES groups have been speculated. Some studies suggest that low SES groups may be overrepresented in incidence statistics. Those with fewer than 12 years of education are significantly more likely to perceive that foodborne illness is very common when compared to those with more education.[79] Low SES groups may, therefore, tend to believe that a bout of gastrointestinal distress is due to foodborne illness. It is possible that low SES groups, particularly those with less education, are less able to gauge the severity of the infection and may not be aware of symptom management methods.[66] Furthermore, it is possible that the economic hardship incurred as a result of missed time at work may cause more low income individuals to present to their physicians in order to expedite their recovery. After conducting a telephone survey of employed persons in Sweden (N=3801), Aronsson et al. (2000) found that low income was associated with a high likelihood of presenting to work while sick.[80] The results of this study and others also support a negative association with care-seeking behavior and education level.[64, 66, 81] Overall, these studies suggest that fewer years of education and lower social class independently increase the likelihood of seeking medical care for gastrointestinal infection.

However, other studies suggest that high SES groups may be overrepresented in incidence statistics. It is possible that since lower SES groups tend not to have health insurance or financial means to seek medical care in the event of illness, the ratio of HSES cases to LSES cases may be skewed in the opposite direction. Access to healthcare may be an important influence on rates of reported bacterial infection. In an economy without universal health care coverage, propensity to seek care for GI infection has been associated with having health insurance.[64] Chang et al (2009) identified lower rates of shigellosis and salmonellosis in communities with high rates of unemployment. The authors speculate that the reduction in access to health care due to lack of employment may lead to underdetection of disease in unemployed individuals.[73] Furthermore, when Simonsen et al monitored incidence of foodborne illness in the entire population of Denmark (5.3 million people) between 1993 and 2004, they found that risk of infection significantly increased with income group.[81] Infections were confirmed upon visit to clinics. Denmark offers free public healthcare, providing a mechanism to control for healthcare access. In this study income was still positively associated with gastrointestinal infection.

1.3.3 Factors affecting exposure to foodborne pathogens across socioeconomic groups

Differences in food access, diet composition, food safety knowledge and food-handling behaviors suggest that there might be a higher risk of illness in low income groups than high income groups.

- **Differential retail access.** Access to particular food retail locations and diet composition can affect the degree of exposure to foodborne pathogens. Differences in the local food environments accessible to groups of varying SES may be a cause of differential incidence of foodborne illness. Research continues to demonstrate that low income groups have access to fewer supermarkets[47] and more independent food markets [51] than their high income counterparts. Certain food environment profiles may play a role in the prevention of foodborne illness in local patrons by providing access to safe food. Findings from a recent study published by this laboratory suggests that risk of foodborne illness as measured by bacterial counts, conferred by ready to eat items at independent food markets is higher than risk conferred by items at chain supermarkets in low income areas of Philadelphia PA.[82] Since LSES areas are more likely to have greater numbers of grocery stores than supermarkets,[51] this may increase residents' exposure to foodborne pathogens, suggesting that high income groups in Philadelphia may have access to safer foods than low income groups.

- **Disparities in diet composition.** However, diet may also play a role in the observed increased incidence of gastrointestinal infection in high income groups. Three dietary influences have been identified as having an impact on exposure to foodborne pathogens.

Cost. Foods that are most susceptible to spoilage by bacteria and mold tend to have high levels of free water (water activity).[83] The percent of water by weight of a food, known as energy density, is generally inversely related to its cost.[2] It has been suggested that since the cost of low energy-density, fresh food is prohibitively expensive to low income groups, foodborne illness risk may increase in high income groups as a result of consumption of fresh food as opposed to frozen[81], or heavily processed foods.

Consumption of raw/undercooked food. A few studies have confirmed that high SES groups are more likely to consume high risk foods than low SES groups. Some studies have shown a link between education level and raw food consumption. Klontz et al (1995) performed a telephone survey (N=1620) to assess the prevalence of consumption of raw or undercooked animal protein. They found that those with more than a high school education reported significantly higher frequency of raw egg, clams/oysters, fish and undercooked hamburger consumption than those with less education.[84] Other studies confirm that the practice of serving/consuming thoroughly cooked hamburgers declines with increasing years of education [85] and that those with advanced degrees are more likely to consume undercooked eggs than those with less education.[79]

Income has also been positively associated with consumption of undercooked animal protein. In addition to finding that college-educated individuals were more likely to consume undercooked hamburger than those with less education, Shiferaw et al (2000) found that those with incomes greater than $100,000 per year reported higher frequency of “pink” hamburger consumption compared to those earning less.[86] In an analysis of the food safety questions in the Behavioral Risk Factor Surveillance System (BRFSS) administered to roughly 19,300 respondents over 7 states, Yang et al (1998) also found that the likelihood of undercooked hamburger consumption increased with both income and years of education.[87] These findings were confirmed by a meta-analysis of 20 studies, which found that greater percentage of high income groups reported eating undercooked ground beef and shellfish compared to low income groups. The direction of the relationship was similar for high school education also.[88] It is suggested that this behavior may be more common in high SES groups due to the relatively high cost of these food items (sushi, raw shellfish).[86] Additionally, the behavior may be based on belief that the benefits of the "culinary experience" outweigh possible adverse effects, that one has "sufficient knowledge to control the degree of risk",[84] or that foodborne illness is not very common.[79]

Consumption of exotic foods while on travel. The finding that foodborne illness risk is positively related to SES may be partially explained by the frequency and extent of travel among high income groups. Simonsen et al suggest that high income groups are more likely to travel and this increases their exposure to foodborne pathogens. In one study, infection rates of *Shigella*, a pathogen often "acquired through foreign travel", were two times higher in the high income group than in the reference income group.[81]

Differential food safety practices. Food safety practices of U.S. residents, in general, are less than ideal. Data from phone surveys of a nationally representative sample (N= 1,620) indicate that only 66% of participants perform safe practices for hand washing, cross-contamination prevention and thorough cooking of meat.[85] A more recent telephone survey of 7,493 US citizens revealed that 93% of all respondents reported "always or almost always" washing hands and cutting boards after handling raw meat.[86] Though this may indicate that behaviors may be improving in general, recent research has revealed differences in food safety knowledge and practices across groups. Therefore, a factor that may increase risk of foodborne illness in low SES areas is that low income groups demonstrate less food safety knowledge and/or behaviors compared to high SES groups.

A number of studies have revealed differences in food safety knowledge and practices across populations of varying education and income levels. People with more than 12 years education report more food safety knowledge than groups with less education.[85, 88] Additionally, in a survey of almost 1,600 limited income, young female WIC participants, Kwon et al found that those with less than a high school education had both significantly lower food safety knowledge and behavior scores than those with more education.[89]

Some studies have found that the relationship between SES and food safety behavior is not well defined, however. Shiferaw et al (2000) performed telephone surveys on randomly selected residents of FoodNet states (N=7,493). They found that though people with less than 12 years of education were likely to report not washing hands or cutting boards after handing raw meat, a similar percentage of those with incomes greater than $100,000 also report these behaviors.[86] Similarly, participants of a 1999 telephone survey in Kentucky with the lowest and highest incomes reported high confidence in the nation's food supply and this was associated with the practice of unsafe food behaviors.[79] With regard to specific behaviors, authors found that those with more income and education were more likely to have a food thermometer but more likely to behave unsafely when handling raw meat compared to those with less than a college degree. In contrast, those with high incomes were more likely to practice safe refrigeration techniques than low income individuals.[79] Another study failed to find a difference between reported use of dirty cutting boards between high education and low education groups.[84]

It is important to note that enhanced food safety knowledge is not necessarily related to improved food safety behaviors. A nationally representative sample was surveyed by telephone to assess pathogen awareness and food safety knowledge and behaviors. The researchers found that though there was a general disparity between knowledge and practice of associated behaviors, one of the groups with the largest disparities had the highest level of education. For example, knowledge of hand washing was highest among highly educated individuals, but reported performance of the practice did not differ across education levels. Additionally, years of education was positively associated with increased understanding of thorough meat cooking, but the practice of consuming thoroughly cooked meat was negatively associated with years of education.[85] This finding was confirmed by a meta-analysis of 20 consumer food safety knowledge/behavior studies. The meta-analysis showed that those with less education report executing safer handling practices than those with more education but those with less education knew the least about food safety practices. This finding led the authors to infer that high education consumers were cognizant of potential risk but chose to ignore it. They also inferred that low-education consumers were "unwittingly following" food safety behaviors. Ultimately the authors concluded that there is very little correlation between food safety knowledge and behavior, suggesting that "knowledge is a poor indicator of actual behavior."[88]

However, it is likely that the discrepancy between lack of food safety knowledge and reported increased frequency of food safety practices may be the result of disparate reporting by low SES individuals. In weight loss studies, it has been shown that participants under report total calories consumed[90-91] and that this phenomenon is a result of participants' perception of what is "socially desirable." [91] Additionally, one study found that among normal weight women, underreporting of intake was greater among less educated participants. It may be that low SES groups over-report socially desirable food safety behaviors, given that they know very little about the reasons for their practices. Indeed, behavioral studies have repeatedly demonstrated that participants often feel the need to over report practices that are deemed to be good. [92-93] Therefore, it is possible that though high SES groups are knowledgeable but decide against, unconsciously or consciously, safe food practices, low SES groups may in fact be less knowledgeable and have worse safe-food handing behaviors.

In summary, findings on actual/estimated FBI incidence and food safety knowledge and behaviors across SES levels are inconsistent at best. Though the dietary practices of high SES groups might increase risk for FBI, low SES groups may be at greater risk for FBI given both access to a less-favorable food retail profile and a deficit in food safety behaviors and knowledge.

1.3.4 Assessment of community FBI risk

The reduction of any potential disparities in food borne illness is a vital task. So vital, that it has been deemed a major public health issue and is a focus of the Healthy People 2010 initiative.[94] After controlling for pre-existing conditions, gastrointestinal infections have been found to be associated with increased risk of short-term mortality.[95] Reducing rates of foodborne illness would enhance longevity of community residents.

Risk assessed by health inspections. Identifying risk for foodborne illness inside the home may be the responsibility of the resident, but assessing risk for foodborne illness conferred by food-for-purchase outside the home is the responsibility of the local health inspector.

Over 85% of State and Territory health departments in the U.S. conduct inspections of foodservices based on guidelines presented in the USDA's Food Code. [96] The purpose of inspections is to minimize risk, defined as the "likelihood that an adverse health effect will occur within a population as a result of a hazard in a food." A critical violation of the food code is defined as an infraction that is "more likely than other violations to contribute to food contamination, illness, or environmental health hazard."[96] Foodservices with relatively few critical infractions may be considered to offer safer food than those with higher rates of violations.

Relationship between inspection scores and outbreaks. Health inspections are meant to examine food safety risk at the retail level, though inspection data may not necessarily correlate to outbreaks.[97] The exact number and type of violation necessary to produce a substantial health hazard is not well defined.[98] Furthermore, assessment of risk via health inspections does not take into account food-handling at home. According to the Institute of Food

Technologists' Expert Panel on Food Safety and Nutrition (1995), occasional illnesses as a result of in-home food preparation are more common than cases recognized as official outbreaks. Less is known, however, about the rate of occasional illness resulting from preparation by foodservices.

Factors impacting sanitation compliance and reported violation rate. A few factors may influence compliance by foodservice operators and violations reported by inspectors. One of the most widely studied factors is the impact of inspection frequency on sanitation compliance. Health departments may define many types of inspections: routine, re-inspection, sanitation inspection as a result of a complaint. Therefore, the frequency of inspection performed at a foodservice establishment is highly variable. It is a common notion, even among inspectors,[99] that inspection scores are a function of inspection frequency – the more an establishment was inspected, the more compliant the facility would be. However, a number of studies have failed to show such a relationship.[99-100] In a Canadian study evaluating the efficacy of more frequent inspections on sanitation compliance, Newbold et al (2008) worked with local health inspectors to randomly assign 374 high-risk category establishments to three, four or five inspections in 2006. They found that an increased number of inspections did not improve sanitation compliance.[99] A number of studies have failed to show that increased inspection rate has any impact on sanitation.[97, 101-102] Furthermore, Corber et al (1984) found that doubling the inspection frequency from 6 to 12 inspections does not improve sanitation compliance.[100] A decrease in number of inspections, however, does indeed negatively impact sanitation compliance. Studies have found that both reducing inspection frequency[103] and increasing time between inspections to greater than one year[104] result in declines of sanitation compliance. Conversely, more inspections may translate to more opportunities to find violations. After a regression analysis of Detroit inspection data, Pothukuchi et al (2008) found that each additional routine inspection performed resulted in one additional critical violation.[105]

The results from studies discussed above suggests that while there may be a decline in sanitation compliance if inspection frequency is reduced from the status quo, there is no association between increased inspection frequency and reduction in violations

There may be other possible influences on sanitation compliance as well. The size of the establishment may impact the degree of compliance. In a study performed in the UK, small and medium sized establishments, generally considered to be less compliant with sanitation regulation, were surveyed to elucidate barriers to compliance. The authors found that though most vendors cited lack of money and time as the greatest barriers, sanitation compliance was not prioritized due to a lack of understanding and knowledge, lack of motivation in dealing with compliance issues and lack of trust in regulations and inspectors.[106] Though the study focused on sentiment among small establishment operators, the authors noted that larger establishments are often subject to corporate sanitation standards and may employ individuals solely to ensure proper execution of regulations.

The demographics of the surrounding area may also be associated with violation rate. Pothukuchi et al (2008) examined the relationship between inspection scores and external factors including area poverty level using 2004 inspection data in Detroit. Regression showed that percent of individuals below poverty at the Zip code level significantly affected critical violations reported for an inspection. Specifically, for each additional 10% of persons below poverty, one could expect an increase of 0.6 critical violations.[105]

1.4 Geographic Information Systems and public health

Recently, the ability to pinpoint health outcomes to specific geographic locations has improved greatly. Such geographic analysis is facilitated by Geographic Information Systems (GIS) technology. GIS use is multidisciplinary and has proved useful in mapping community disease risk[107] and food borne illness outbreaks.[108] This technology's utility in food safety research lies in its ability to relate tabular data to geographic entities and perform geospatial analyses. These features can facilitate the detection of environmental gradients.

GIS allows for the integration and analysis of geographic data, such as coordinates and area perimeters, and tabular data (i.e. attributes of geographic data points). Data is imported into mapping software in layers, where each layer represents a different visual component of the map. Shape files are layers which provide visual output of coordinates and area perimeters on the map. There are three types of shape files, namely point, line, and polygon files, and each represents a distinct data type. Points are discrete, single XY coordinates (e.g., locations of stores) while lines and polygons represent coordinate ranges (e.g., roads and census tract perimeters, respectively).

Though tabular data may be added as a layer of the map file, it does not represent a specific shape and will therefore not be displayed on the map. Tabular data provides the attributes that are to be associated with corresponding shape files. This relationship allows the GIS user to query the data, selecting shape files with attributes of interest (e.g., selecting census tracts with less than 1000 residents).[109]

GIS programs perform three common types of spatial analysis: proximity, overlay and network analyses. As its name implies, a proximity analysis provides information on the distance between features and number of features within a given distance. An overlay analysis can determine the overlapping features (and quantity of overlap) between two or more layers. Finally, a network analysis provides information on the linear relationship between features (e.g., shortest travel route between two points in a metropolitan area).[109]

GIS may be applied to a number of disciplines. In addition to fields where the application of GIS may be inherent, such as city planning and ecological studies, GIS has recently been used to visualize, quantify and analyze geographic components of health research. Studies have ranged from analysis of geographic variation in the use of surgical procedures[110] and prevalence of drug use across school districts[111] to examination of the relationship between ethnicity, low birth weight and area SES[3] and following the movement of the AIDS epidemic.[112] Most recently, GIS has been utilized to examine the relationship between area-based socioeconomic measures and incidence of salmonellosis.[76] These studies demonstrate the wide range of uses for GIS.

The existence of variations in health outcomes across different communities is of interest to many groups. Healthy People 2010 is a program put forth by the Department of Health and Human Services to address and eliminate the presence of disparities between certain groups for a number of health measures.[113] Research by Whitman et al[114] has shown that GIS can be a valuable tool in the analysis of health disparities. Their research, conducted using six diverse communities in Chicago, examined the change in fourteen health status indicators from 1989-90 to 1999-2000. The authors found disparities in changes in health outcomes where area income was generally associated with favorable changes in health status indicators.[114] This study provides evidence to support the relationship between income and health and demonstrates the utility of GIS technology in health disparity research.

CHAPTER TWO: FOOD ACCESS AND POVERTY

Comparison of Two Datasets to Assess Food Access in Areas of Different Socioeconomic Status in Philadelphia, Pennsylvania

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Abstract

This research utilized GIS technology to compare two databases and investigate how community poverty level relates to food access in Philadelphia, PA. Retail food listings were purchased from Dun and Bradstreet (D&B) (N=4,263) and determined using inspection records from the Philadelphia Health Department (PDPH) (N=5,847). Facilities of interest were identified by NAICS code and by keyword, respectively. Addresses were geocoded to census tracts in Philadelphia, PA. Census tracts (N=368) were divided into quintiles using Census Bureau poverty data. GIS overlay analysis was used to group locations within tracts. Chi-square statistic was utilized to test interaction between poverty and store type distribution. Using either database, a significant ($p<0.05$) interaction was found between poverty and the distribution of food markets, indicating that proportions of all grocery stores (including corner markets) were highest in high poverty (low income) areas. Further examination of D&B revealed 11.8% of markets in low poverty (high income) areas to be chain markets compared to only 1.5% of markets in high poverty (low income) areas. Using PDPH, supermarkets alone made up 17.6% of markets in lowest poverty (high income) areas and only 4.4% in the highest poverty (low income) areas. There was a significant interaction between poverty and the distribution of fast-food and full service restaurants using PDPH ($p=0.001$) but not D&B ($p = 0.065$). Fast-food comprised 49.0% and 45.3% of restaurants in highest and lowest poverty areas, respectively. This study demonstrates not only differential access to food for different populations but also the need to investigate different sources of data for food access research.

Given that multiple data sources are being utilized to estimate the effect of poverty on food access and food access on overall health, this research utilized GIS technology to compare retail foodservice listings from two commonly utilized sources, the municipality's health department listings and a commercial, pay-for-access database, and investigate how community poverty level relates to food access in Philadelphia, PA. The purpose of this research was twofold. First, we sought to compare the results of the Department of Public Health and Dun and Bradstreet in analysis of access to healthy food. We hypothesized that both datasets would produce comparable results (no difference between food access as assessed by each dataset). The second purpose was to examine the relationship between poverty and access to store types in Philadelphia. Similar to other studies, we also hypothesized that low income groups would have both greater travel distance to and fewer supermarkets within their neighborhoods, compared to high income groups. We hypothesized that low income groups would have greater access to unhealthier food, based on a greater number of, and shorter travel distance to fast food restaurants than high income groups.

Methods

This comparative and correlational study was conducted in 2009 and utilized the following data sources: Demographic information from the Census Bureau (2000 Census survey), retail listings inspected between 7/05 and 2/08 from the Philadelphia Department of Public Health and retail facilities on record during the fourth quarter of 2007 (Dun and Bradstreet).

Data acquisition and management. Land area and demographic data were acquired from the United States Census Bureau.[115] Data was collected at the level of the census tract. The total tract area and tract land area were collected from the Census Bureau in square feet. Demographic information included the total number of residents per tract, as well as percent of individuals below poverty per tract.

There are a total of 381 census tracts within Philadelphia County. A number (n=11) of tracts represent areas with populations of zero (tracts 24, 43, 49, 50, 52, 57, 58, 59, 68, 74, 124), leaving a total of 370 tracts with populations greater than zero. The (n=11) tracts with populations of zero were excluded from any analyses as population data is needed to determine poverty level. Two additional tracts were excluded due to null income data. Remaining census tracts (N=368) were divided into quintiles using Census Bureau poverty data to facilitate comparison of groups based on neighborhood poverty, defined as the percentage of residents living below poverty.[47] Quintiles included the following poverty ranges: 0%-9.9% (lowest poverty), 10.0-19.3%, 19.8-30.3%, 30.4-44%, and 44.8-78.0% (highest poverty). Average total population is not significantly different between categories ($p = 0.91$). However, poverty categories differed significantly on percent population living at or below poverty and median income ($p<0.01$). Characteristics of each poverty category can be found in Table 1.

Electronic maps containing geographical features of Philadelphia County are publicly available and were obtained from a databank of state information (New Urban Research). Shape files including location, shape of census tracts (polygon data), size and shape of county (polygon data), and location, length and cardinal direction of roads and streets (line data) were imported into mapping software (ArcView 9.3, ESRI, Redlands, CA). Maps were projected using a projected coordinate system (NAD 1983 State Plane Pennsylvania South FIPS 3702).

Retail food listings were purchased from Dun and Bradstreet (D&B) and determined using health inspection records from the Philadelphia Department of Public Health (PDPH). A list of establishment types of interest was purchased from D&B during the fourth quarter of 2007. Establishment types were identified by associated primary North American Industrial Classification System (NAICS) code. NAICS codes selected for analysis represent supermarkets and grocery stores, convenience stores, fast-food/take-out facilities, full service restaurants, and

Table 1. Characteristics of Census Tracts by Poverty Category

	Neighborhood Poverty				
	1 **Low** **(*n*= 85)**	**2** **Low-medium** **(*n*= 95)**	**3** **Medium** **(*n*=80)**	**4** **High-medium** **(*n*=67)**	**5** **High** **(*n*= 41)**
Characteristics	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**
Total Pop	3578.1 (2412.7)	4437.8 (2397.1)	4341.4 (2225.2)	4284.1 (2091.1)	3840.5 (2479.1)
Percent Below Poverty*	5.8 (2.9)	14.1 (2.8)	24.9 (3.1)	35.7 (3.9)	52.6 (7.7)
Median Household Income*	$51,989 ($23,037)	$37,339 ($10,604)	$28,218 ($5,251)	$20,862 ($4,037)	$13,929 ($3,446)
Tract Size [square miles]*	0.49 (0.36)	0.32 (0.26)	0.28 (0.15)	0.23 (0.12)	0.25 (0.21)
Population density (persons per square mile)*	9335.1 (6929.1)	17862.5 (10264.9)	18397.4 (9049.8)	21458.1 (10990.5)	17932.9 (9174.4)
Vehicles per household*	1.36 (0.26)	1.05 (0.26)	0.83 (0.18)	0.64 (0.16)	0.52 (0.16)
Percent of Households without Private Transport	9.9	20.2	33.0	39.5	42.9

No significant difference in population between groups (p = 0.91).
*Percent below poverty, median household income, tract area, population density and vehicles per household significantly different between groups (p<0.001).

meat, fish or produce markets (Appendix A, Table 9). Proprietary D&B information facilitated the designation of chain/independent status of foodservices.

A listing of foodservice establishments was compiled from data available on the Philadelphia Department of Public Health (PDPH) website.[116] Listings reflect establishments in operation between July 2005 and February 2008 and included establishment name, address, general type (e.g. "prepared food take-out" or "restaurant, eat-in"), inspection dates and any observed critical health code violations. Data was transposed from original PDF format to Excel.

Original store classifications, as determined by heath inspectors, were largely inconsistent. Stores were recoded into categories based on keyword. For example, *grocery* included food services with the following words in their names: market, grocer, grocery, groceries, food center, mkt, food store, food market, food mart, bodega, tienda, farm, and some combination of "fish/meat + fruit/vegetable" (Appendix A, Table 10). Delis were included in the *grocery* category to facilitate comparison with Dun and Bradstreet, which uses NAICS code 445110 (Supermarket & Grocery [except convenience]). With regard to food services with compound keyword names, word order was utilized to determine store category. For example, "bakery & café" was classified as *other*, while "café & bakery" was classified as *restaurant, eat-in.* Foodservices that were not classified included those with ambiguous keywords such as "kitchen", "place", "house", "store", and "restaurant".

Food services at private locations were excluded from analysis. This included any location where patrons must pay for admission (zoo, stadiums, airport), institutions (penal facility, schools), or special membership is required for entry (private club).

Facilities of interest were identified by NAICS code in D&B and by keyword in PDPH. The vendor categories of interest were as follows: Grocery/Supermarket, Convenience, Fast-food/take-out, Full-service restaurant, Produce markets, and Meat/Fish markets. To further facilitate comparison of "grocery/supermarkets" across datasets, the category was broken down into "supermarkets" and "grocery" using keyword in PDPH and information pertaining to chain status in D&B. Using D&B, chain groceries were considered “supermarkets” while independent/non-chain groceries were considered “groceries”.

Mapping. The process of geocoding assigns a longitude and latitude (XY coordinates) to map addresses as points. In order to geocode addresses, an address locator was created within ESRI ArcCatalog, using the network of Philadelphia County’s road and streets (Census 2000 TIGER/Line) as reference file. The locator style was *US Streets with Zone*.

The D&B dataset included 4799 total establishments downloaded from Dun and Bradstreet based on primary NAICS codes and run through address locator. After first geocoding attempt, 51 establishments were removed because they failed to map at all. Of the 4748 mapped facilities, 21 establishments were eliminated for various reasons (N=5 duplicates, N= 16 airport locations). A spatial join was conducted using 4727 total geocoded establishments and underlying census tracts. Sixty two establishments were removed from dataset because they fell within tracts with zero median income (industrial/commercial). Of 4665 establishments that were successfully geocoded to tracts with income data, 402 were not classified under NAICS codes of interest and removed from analysis (e.g., salon, game room, and specialty food/confection). A final total of 4263 establishments were included in analysis (Table 2).

The PDPH dataset contained 15,067 establishments in total. Establishments were cross referenced using facility name, type and address to check for duplicates. Three hundred and ninety nine duplicates were removed resulting in 14,668 unique listings.

The PDPH dataset was run through the geocoder’s address locator script. Of the unique records, 619 (4.22%) did not geocode on first pass. Original addresses were confirmed and corrected using Google maps. Of unmatched listings, 237 were listed with incorrect zip codes while 272 required minor street address modifications (e.g. typographical or spelling error, cardinal direction missing) while 110 addresses (0.75%) were not able to be located using Google maps and were therefore left uncorrected. Some locations were not able to be geocoded on the basis of street address. Under this circumstance, the addresses were geocoded to the nearest street intersection.[47]

Once corrected, the address file with 14,558 establishments was rerun through address locator. The address points associated with violations were joined based on spatial location to the census tract level income data. Addresses which were geocoded to tracts with null data for median income were excluded after final geocoding (N=407). After these exclusions, 14,151 unique records remained.

Establishments were excluded based on public/private designation. Private establishments (n=3,292) were excluded from analysis (Appendix B, Table 13). Facilities were then classified by keyword, as outlined above. Of 10,859 public establishments, 14.1% (n=1528) were classified as non-retail food establishment (i.e. "other"), 6.4% (n=695) were mobile food vendors, and 25.7% (n=2789) were not able to be classified. Vendors listed as unclassified could not be placed in one category over another with any degree of confidence. Common types of unclassified listings can be found in Appendix A, Table 12. Listings classified as "other" and "mobile food vendors" were excluded from the analysis to facilitate comparison with D&B dataset. The table below (Table 2) shows the distribution of the remaining 5847 facilities by vendor types in the PDPH dataset.

Table 2. Frequency of Foodservice Types in D&B and PDPH Datasets

Category	D&B Database N (% of database total)	PDPH Database N (% of database total)
Convenience Stores	212 (5.0%)	1073 (18.4%)
All Grocery Markets	1049 (24.6%)	2008 (34.3%)
Full Service Restaurants	1669 (39.2%)	935 (16%)
Fast Food Restaurants	1174 (27.5%)	1690 (28.9%)
Meat/Fish Markets	107 (2.5%)	86 (1.5%)
Fruit/Veg Markets	52 (1.2%)	55 (0.9%)
Total Vendors	4263	5847

In both datasets, data for facilities of interest were joined to demographic attributes of the Census tracts in which they fell. The joined data file was then exported for analysis. Tract centroids were determined using ArcGIS and considered to be proxies for the center location of each neighborhood.[47] Centroids were given attributes of closest establishment of interest, including straight line distance to each establishment. Census tracts data were joined with data concerning respective distance to nearest establishment of interest, using both datasets. This file was also exported for analysis.

Statistical analysis. Data analysis was performed using Statistical Package for the Social Sciences (SPSS, Inc. Chicago, Illinois). In order to examine whether poverty category affected the distribution of store types, we used Chi Square statistic. We examined relative distribution (percent) rather than absolute values because the datasets do not represent facilities on record during the same time frame (D&B end of fourth quarter 2007; PDPH 7/2005-2/2008).

Since the data concerning distance to nearest store were not normally distributed, and could not be normalized by transformation (Kolmogorov-Smirnov $Z = 1.74$; $p = 0.005$; Appendix A, Figure 2), the data were subjected to Kruskal-Wallis non-parametric analysis of variance to evaluate whether distance to store of interest was significantly different across poverty levels. A p-value of < 0.05 was considered statistically significant in all analyses. Effect size is reported using partial eta-squared value.[117]

Results

We examined the distribution of PDPH listings that were not able to be identified based on keyword across poverty quintiles. Across all groups, roughly 25.7% of listings could not be classified (n=2789) while 74.3% of listings were able to be classified by keyword (n=8070). The interaction between poverty and the distribution of classified and unclassified listings reached statistical significance (p=0.043) where poverty category 2 (medium-high income) displayed the greatest percentage of unclassified vendors (27.5%) and the middle income group (poverty category 3) had the smallest proportion of unclassified vendors (23.9%) (Appendix A, Table 11).

Though the interaction reached significance, the actual difference between these categories is small. Therefore, subsequent analyses are based only on classified listings.

Supermarkets/groceries vs. convenience stores. Using either database, a significant ($p<0.001$) interaction was found between poverty and the distribution of food markets, indicating that percentages of all grocery stores (including corner markets) were highest in high poverty areas. Use of the D&B dataset revealed that, in the lowest and second lowest poverty (high income) areas, 75.3% and 75.6% of markets were supermarket/groceries, respectively, while 85.4%, 86.8% and 90.1% of markets in poverty categories 3, 4 and 5 (low income) were supermarket/groceries, respectively (Table 3). Chi-square analysis was significant at $p<0.001$ ($\chi^2=26.92$, df=4). Similarly, use of the PDPH dataset also revealed that, in the lowest and second lowest poverty categories (highest income), 43.4% and 53.1% of markets were supermarket/groceries, respectively. In poverty categories 3, 4, and 5, supermarket/groceries represented 67.2%, 73.2% and 74.1% of markets, respectively (Table 3). Chi-square analysis was significant at $p<0.001$ ($\chi^2=142.53$, df=4).

Supermarket vs. Grocery. Using either database, we found a significant ($p<0.001$) interaction between poverty and the distribution of supermarkets and groceries such that two highest poverty categories contained the smallest percentages of chain/supermarkets. The D&B dataset revealed that poverty categories 3, 4, and 5 (medium to low income) had the smallest distribution of supermarkets (2.7%, 2.2%, 1.5%, respectively) compared to the two lowest poverty categories (5.4% in poverty category 2; 11.8% in poverty category 1) (Table 4). Chi-square analysis was significant at $p<0.001$ ($\chi^2=25.141$, df=4). Using the PDPH dataset, poverty categories 1 and 3 (high and medium income) had the highest proportion of supermarkets (17.6% and 9.6%, respectively) while categories 2, 4 and 5 had the lowest (7.9%, 6.5%, and 6.2% respectively) (Table 4). Chi-square analysis was significant at $p<0.001$ ($\chi^2=20.301$, df=4).

Fast food vs. full service restaurants. There was a significant interaction between poverty and the distribution of fast-food and full service restaurants using PDPH ($p=0.001$) but not D&B (p = 0.065). Using PDPH, fast-food comprised 45.3% and 39.7% of restaurants in poverty categories 1 and 2 (highest income), respectively, and 49.9%, 50.2%, and 49.0% of restaurants in middle to lowest income groups, poverty categories 3, 4, and 5 (Table 5). Chi-square analysis was significant at $p<0.001$ ($\chi^2=39.847$, df=4). Analysis of the D&B dataset, which yielded a statistically insignificant result (p=0.065), revealed a decrease in proportion of fast food establishments as poverty increases. In the lowest poverty (highest income) group, 43.6% of restaurants were fast food while 35.8% of establishments in the highest poverty (lowest income) group were fast food. Again, the interaction between poverty and restaurant distribution using the D&B dataset was not significant ($\chi^2=8.862$, df=4, p=0.065) (Table 5).

Distance to convenience, grocery, and supermarkets. Average distance, in miles, to convenience (D&B = 0.41$\pm$ 0.28; PDPH= 0.22$\pm$ 0.17), grocery (D&B = 0.24 $\pm$ 0.23; PDPH= 0.22 $\pm$ 0.23), and supermarket (D&B = 0.83 $\pm$ 0.42; PDPH= 0.48 $\pm$ 0.31) were calculated across all census tracts (n=368) (Appendix A, Figure 3). Distances to establishments were analyzed via Kruskal-Wallis nonparametric analysis of variance. Analysis revealed a significant difference in distances by poverty levels to convenience, grocery and supermarkets ($p<0.001$; partial Eta squared = 0.207, 0.279, 0.202, respectively) using PDPH, and convenience stores ($p<0.001$; partial Eta squared 0.113) and groceries ($p<0.001$; partial Eta squared 0.211) but not supermarkets (p = 0.289) using D&B.

Post-hoc pair-wise multiple comparisons were conducted using the Games-Howell post hoc test which is appropriate for handling unequal variances[118] and unequal sample sizes.[119-120] Presence of unequal variances was confirmed by Levine's test ($p <0.001$) and further supported use of Games-Howell procedure. Games–Howell post hoc tests revealed significantly greater

Table 3. Distribution of Convenience, Supermarket/Grocery Stores by Poverty Category

	Neighborhood Poverty				
	1 **Low** **(*n*= 85)**	**2** **Low-medium** **(*n*= 95)**	**3** **Medium** **(*n*=80)**	**4** **High-medium** **(*n*=67)**	**5** **High** **(*n*= 41)**
Characteristics	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**
D&B[a]					
Convenience	36 (24.7%)	66 (24.4%)	44 (14.6%)	42 (13.2%)	24 (10.9%)
Supermarket/ Grocery	110 (75.3%)	204 (75.6%)	258 (85.4%)	277 (86.8%)	196 (90.1%)
PDPH[b]					
Convenience	155 (56.6%)	291 (46.9%)	249 (32.8%)	237 (26.8%)	141 (25.9%)
Supermarket/ Grocery	119 (43.4%)	329 (53.1%)	510 (67.2%)	647 (73.2%)	403 4.1%)

a) $\chi^2 = 26.920$, df = 4, $p < 0.001$
b) $\chi^2 = 142.532$, df = 4, $p < 0.001$

Table 4. Distribution of Supermarket and Grocery Stores by Poverty Category

	Neighborhood Poverty				
	1 Low (*n*= 85)	**2 Low-medium (*n*= 95)**	**3 Medium (*n*=80)**	**4 High-medium (*n*=67)**	**5 High (*n*= 41)**
Characteristics	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**
D&B[a]					
Grocery (non-chain)	97 (88.2%)	193 (94.6%)	251 (97.3%)	270 (97.8%)	193 (98.5%)
Supermarket (chain)	13 (11.8%)	11 (5.4%)	7 (2.7%)	6 (2.2%)	3 (1.5%)
PDPH[b]					
Grocery	98 (82.4%)	303 (92.1%)	461 (90.4%)	605 (93.5%)	378 (93.8%)
Supermarket	21 (17.6%)	26 (7.9%)	49 (9.6%)	42 (6.5%)	25 (6.2%)

a) $\chi^2 = 25.141$, df = 4, $p < 0.001$
b) $\chi^2 = 20.301$, df = 4, $p < 0.001$

Table 5. Distribution of Fast Food and Full Service Restaurants by Poverty Category

	Neighborhood Poverty				
	1 Low (*n*= 85)	**2 Low-medium (*n*= 95)**	**3 Medium (*n*=80)**	**4 High-medium (*n*=67)**	**5 High (*n*= 41)**
Characteristics	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**
D&B[a]					
Full Service	299 (56.4%)	528 (56.7%)	324 (58.3%)	272 (61.4%)	246 (64.2%)
Limited Service/ Take Out	231 (43.6%)	403 (43.3%)	232 (41.7%)	171 (38.6%)	137 (35.8%)
PDPH[b]					
Full Service	432 (54.7%)	898 (60.3%)	540 (50.1%)	464 (49.8%)	418 (51.0%)
Limited Service/ Take Out	358 (45.3%)	592 (39.7%)	538 (49.9%)	468 (50.2%)	401 (49.0%)

a) χ^2= 8.862, df = 4, p =0.065
b) χ^2= 39.847, df = 4, p < 0.001

distances to convenience stores for the lowest poverty category compared to other groups, using both PDPH ($p<0.001$) and D&B ($p<0.001$) (Table 6). There was also a significant difference between distances to groceries between poverty category 1 and poverty category 2 using both D&B ($p<0.001$) and PDPH ($p<0.001$), and these distances were significantly greater than other groups. Distances to supermarkets were significantly different between poverty category 1 and 2 compared to all groups, using PDPH ($p<0.05$). Analysis of distances to supermarkets did not produce any significant differences using D&B.

Distance to fast food and full service restaurants. Average distance, in miles, to fast food (D&B = 0.23$\pm$ 0.18; PDPH= 0.23$\pm$ 0.18) and full service restaurants (D&B = 0.21 $\pm$ 0.16; PDPH= 0.28 $\pm$ 0.21) was calculated across all census tracts (n=368) (Appendix A, Figure 4). Using both datasets, Kruskal-Wallis analysis revealed a significant difference in distances across poverty levels to fast food ($p<0.001$; partial Eta squared: 0.117 D&B, 0.146 PDPH) and full service restaurants ($p<0.001$; partial Eta squared: 0.114 D&B, 0.133 PDPH) (Table 6).

Games–Howell post hoc tests revealed significantly greater distances to fast food restaurants for the lowest poverty (highest income) category compared to all groups, using both PDPH ($p\leq0.001$) and D&B ($p<0.001$). Similarly, Games–Howell post hoc tests also revealed significantly greater distances to full service restaurants for the lowest poverty (highest income) category compared to all groups, using both PDPH ($p\leq0.001$) and D&B ($p<0.005$).

Discussion

Aspects of the built environment, including the retail food landscape, are known to affect health of residents.[18, 33, 36, 121-122] Studies measuring the local food environment often rely on various secondary data sources to supply information on retail food establishment listings. There is data to suggest that some of the sources used in exploring community food access may produce results inconsistent with other sources or methods.[59, 61] This research examined the food environment in Philadelphia and whether use of two available databases of retail food sources results in different information regarding the food environment.

Table 6. Distance to Stores by Poverty Category and Dataset

	Neighborhood Poverty				
	1 Low (*n*= 85)	**2 Low-medium (*n*= 95)**	**3 Medium (*n*=80)**	**4 High-medium (*n*=67)**	**5 High (*n*= 41)**
Database, *Store type*	**Mean Distance, mi^2 (SD)**	**Mean Distance, mi^2 (SD)**	**Mean Distance, mi^2 (SD)**	**Mean Distance, mi^2 (SD)**	**Mean Distance, mi^2 (SD)**
Dun and Bradstreet					
Convenience	0.58 ± 0.36**	0.37 ± 0.26	0.36 ±0.21	0.34 ±0.19	0.33 ±0.23
Grocery (Independent)	0.43 ± 0.31**	0.25 ± 0.20*	0.17 ± 0.13	0.14 ± 0.10	0.17± 0.21
Grocery Chain [a]	0.81± 0.40	0.76 ± 0.37	0.86 ± 0.46	0.88 ± 0.43	0.89± 0.43
Philadelphia Department of Public Health					
Convenience	0.36 ±0.24**	0.21± 0.15	0.19 ±0.11	0.16 ±0.09	0.16± 0.1
Grocery	0.43 ±0.29**	0.21 ±0.18*	0.15 ±0.12	0.10 ±0.09	0.14 ±0.22
Supermarket	0.70 ± 0.37**	0.51 ±0.29*	0.38 ±0.25	0.34± 0.20	0.32 ±0.20
Dun and Bradstreet					
Fast Food	0.34±0.23**	0.20±0.17	0.19±0.12	0.19±0.12	0.20±0.13
Full Service	0.30±0.19**	0.21±0.17	0.19±0.11	0.15±0.12	0.17±0.13
Philadelphia Department of Public Health					
Fast Food	0.35±0.23**	0.22±0.18	0.18±0.12	0.17±0.10	0.17±.13
Full Service	0.42±0.27**	0.25±0.20	0.23±0.15	0.22±0.14	0.25±0.15

Significant differences between poverty categories indicated with ** and * where applicable ($p \leq 0.005$).
[a.] No significant difference between groups ($p = 0.289$; $\chi^2 = 4.98$, df = 4).

Both datasets produced significant interaction such that two highest poverty (lowest income) groups had lowest proportion of chain supermarket indicating that higher poverty groups have reduced access to chain supermarkets establishments. Percent of non-convenience store markets that were supermarkets ranged from 11.8% for the lowest poverty level to 1.5% in the highest poverty level in D&B, and 17.6% in the lowest poverty group to 6.2% for the highest poverty group using PDPH. The two datasets differed, however, with respect to the linearity of the resulting relationships. Using D&B there was a clear linear decrease in proportion, while PDPH revealed that the second greatest proportion of supermarkets was in poverty category 3 (middle income). This suggests that the relationship between mid-level poverty groups and degree of supermarket access may be different depending on what data source is used.

Comparison of restaurant distribution. Comparison of the distribution of fast food and full service restaurants across poverty levels revealed that the general direction of the relationship was in accordance with the literature using PDPH only.[13, 54-56] Use of PDPH confirmed previous findings that high poverty groups have greater access to fast food establishments than lower poverty groups (49% and 45.3% of restaurants, respectively). Using D&B, the proportion of fast food restaurants trends in the opposite direction than expected; there was a linear, but slight, decrease in proportion of fast food establishments in higher poverty areas, such that 43.6% of restaurants in the lowest poverty group were fast food establishments while only 35.8% of restaurants were fast food in the highest poverty group. However, there was not a significant interaction between poverty and the distribution of fast food or full service restaurants. These results highlight disparities between the two datasets with respect to fast food distribution across poverty levels.

Comparison of distance to markets. Across all groups, the relative relationship between distance to markets was maintained by both datasets. That is, in general, using both

D&B and PDPH, independent groceries were closer than convenience stores, which in turn, were closer than any chain grocer/supermarket. Differences in travel distances across poverty groups were similar between datasets for convenience stores and grocery stores. Using both datasets, the lowest poverty (highest income) group displayed distances to convenience stores that were significantly greater than other poverty groups. Also using both datasets, poverty categories 1 and 2 (high income) were significantly different from each other and from other poverty groups for grocery stores. That is, though absolute distances were different across datasets, these results show that both data sources produce similar differences between poverty groups for distances to convenience and grocery stores.

The biggest disparity between databases resulted when distances to supermarkets were compared across poverty groups. While PDPH produced a significant difference in travel distance in the lowest poverty group, interestingly, there was not a significant difference in the mean travel distance to supermarkets between poverty categories using D&B. These results indicate that distance to non-chain grocery/supermarket establishments should be interpreted with caution as results can differ depending on the source of the data.

Comparison of distance to restaurants. Across all groups, the relative relationship between distance to restaurants was not maintained across both datasets. That is, using the PDPH dataset, fast food establishments were found to be closer to neighborhood centers than full service restaurants, while fast food establishments were marginally farther from neighborhood centers than full service restaurants using D&B (Appendix A: Figure 4). The two datasets produced nearly identical results for distances to fast food establishment (across all tracts) (D&B 0.2286 $\pm$ 0.178 miles; PDPH 0.2250 $\pm$ 0.180). Additionally, D&B and PDPH produced very similar overall average distance to full service restaurants across all tracts (D&B = 0.21 $\pm$ 0.16; PDPH= 0.28 $\pm$ 0.21). Furthermore, the differences between groups were similar using both data sources, such that the lowest poverty (highest income) group displayed significantly greater distances than any other poverty category for both restaurant types. These results indicate that, in general, the two data sources produce roughly similar results in terms of distance to restaurants.

These results demonstrate that, depending on the store type and metric of interest, the source of the data analyzed may have a significant impact on the interpretation of the consumer experience and subsequent policy development. Since access to private transportation is more common in more affluent areas, the consumer experience in high poverty areas should hold the greatest weight. Access to quality, affordable health food options in supermarkets and reduced access to fast food options are the qualities which facilitate optimal health of residents in the local food environment. In this study, both datasets showed overall reduced percentages of supermarkets in the highest poverty groups compared to lowest poverty groups, though only one dataset showed significantly increased proportions of fast food establishments in high poverty areas. The Dun and Bradstreet dataset failed to produce a significant effect in both the distribution of fast food establishments across poverty levels and differences in distances to supermarkets – effects commonly observed in other studies of other metropolitan areas. Therefore, results from the PDPH dataset more closely resemble results from other studies.[13, 51, 54-56]

There are some limitations with the current study. One limitation is the degree of dataset compatibility. Dun and Bradstreet analysis was based off classification by NAICS and proprietary classifications (i.e., chain/non-chain status), while manual keyword identification was necessary to re-classify vendors and establish uniformity in Philadelphia Department of Health's dataset. We found that the NAICS code "445110: Supermarkets and Other Grocery (except Convenience) Stores" was too broad a category to produce expected results. Within D&B, we utilized information pertaining to chain grocery status to represent "supermarkets". However, it is possible that alternate or additional data points, such as annual sales volume, may have provided a more valid representation. Additionally, to confirm accuracy of, and further validate our findings, future studies may incorporate ground truthing to triangulate results. Lastly, the data sources may not be directly comparable in that their collection periods differ. In the current study, establishment listings were supplied using data available at the fourth quarter 2007 (D&B) and between July 2005 and February 2008 (PDPH), leading to a comparison of crosssectional and longitudinal data. Though population demographics were supplied by the 2000 Census data, demographics have not shifted drastically over the course of 5-8 years. In 2000, 22.9% of individuals in Philadelphia (N= 1,517,550) were living below poverty while 24.3% of individuals (N= 1,448,911) were living in poverty during the last community survey (2006-2008).[115] This indicates that although there was a slight decrease in total population, a larger proportion of residents may be living in areas with reduced access to supermarkets and increased access to fast food. Based on research findings over the last decade, the findings from this cross-sectional, comparison study are highly relevant.

Though the main goal of the current project was to examine the interaction of poverty and food access in Philadelphia, we also sought to compare the food access results obtained from two datasets. In most cases, we observed significant interactions between poverty and establishment type distribution. However, our study is cross sectional in nature and our results can only be interpreted as associations (rather than causality). Furthermore, our results do not reflect the effect of the interaction of poverty and race. Other research has shown that there is a strong correlation between race and poverty ($r=0.70$).[47] The effect sizes of distance results from our study (partial Eta squared ≤ 0.279) indicate that, though poverty accounts for a substantial portion of the variance, it is not likely the sole predictor of food access. Furthermore, this study examined theoretical access to establishments and did not consider non-spatial potential barriers to actual food access such as quality of store contents, area crime rate and store hours. Future studies may examine the effect of race and non-spatial features to further compare available datasets on the distribution of and distance to stores.

Another limitation of the research is the degree that the census tract data may be extrapolated to the individual level. In the current study, neighborhood (tract) poverty was defined by the percent of persons living below the poverty line within a census tract,[47] using the aggregate value for the tract as a proxy for poverty of the individual. Using large-scale, aggregate values may exaggerate the true poverty value at the level of the individual[123] and may be a less consistent predictor of diet than neighborhood income.[122] However, at the level of the census tract, the bias introduced by this aggregate value, with respect to estimating neighborhood poverty has been determined to be minimal.[124]

In summary, this study demonstrates not only the need to investigate different sources of data for food access research, but further confirms differential access to food for different populations in the city of Philadelphia.

CHAPTER THREE: FOOD SAFETY AND POVERTY

Use of GIS Mapping to Determine Relationship between Area Poverty, Critical Health Code Violations and Foodservice Inspection Frequency

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Abstract

There are data to suggest that incidence of food borne illness (FBI) may be associated with an individual's socioeconomic status (SES). However, less is known about the relationship between SES and risk of FBI at the community level. Research suggests community SES may predict access to healthy food given the range of available foodservices available in low income areas. Whether a similar relationship exists for safe food access has not been explored. The ability to pinpoint various indices to specific geographic locations, and detect resulting environmental gradients, is made possible by Geographic Information Systems (GIS). This research investigates the utility of GIS in determining whether community SES relates to access to safe food as measured by foodservice critical health code violations, a proxy of risk for FBI. This study utilized publicly available health inspection records documenting critical health code violations (CHV) for 10,859 foodservice locations collected between 2005-2008. Using an overlay analysis through GIS, CHV were plotted over census tracts in Philadelphia County, Pennsylvania. Census tracts (N=368) were categorized into quintiles based on poverty level, ranging from 5.8% to 52.6% of individuals below poverty. The average CVH rate for all foodservices was 0.765 CHV per inspection. More than half (53.5%) of foodservices had a rate greater than zero CHV per inspection. Rates of CHV (SE) in poverty groups were as follows: 0.93 (0.04) (lowest poverty), 0.73 (0.025), 0.75 (0.024), 0.72 (0.023), and 0.77 (0.025) (highest poverty). The CHV rate of lowest poverty group was significantly greater than that of other groups. The two lowest poverty (highest income) groups also displayed similar and significantly greater number of days between inspections compared to other groups. This research further examines the relationship between socioeconomic status and access to safe food to assess risk of food borne illness.

Disparities in health outcomes exist between residents of high and low income areas. Longitudinal studies using national data have found an association between higher incomes and lower rates of mortality.[4-6] Krieger et al[7] found an association between "fewer economic resources" and "higher mortality rates" after plotting various-cause mortality and cancer incidence data against socioeconomic status. This finding held true independent of race, ethnicity and gender.[7]

Disparities in FBI risk: individual level. Early mortality may be generally associated with available economic resources, but the association between poverty and incidence rates of food borne illness is not well understood. Though it is estimated that over 76 million cases of food borne illness occur annually in the U.S.[62], the proportion of illness experienced by low income groups versus high income groups in the U.S. is unclear.

Some studies have demonstrated an association between lack of economic resources and incidence of foodborne illness. In the UK, incidence of infectious intestinal disease, as measured by hospital admission rates, has been shown to be positively associated with degree of "social deprivation."[70] "Low social class" was also one of factors directly associated with salmonella infection in a study of Italian children.[71] Additionally, certain symptoms of food borne illness (nausea, vomiting, and constipation, but not heartburn or diarrhea) were associated with low socioeconomic status (LSES) in a survey of upper and lower gastrointestinal symptoms in 9000 Australians.[72] In a study exploring the association between demographic variables and confirmed cases of shigella, salmonella, and *E. coli* O157:H7, Chang et al (2009) found that rates of shigellosis and salmonellosis in an area were positively correlated with percent of individuals below poverty.[73]

Differences in food access, diet composition, food safety knowledge and food-handling behaviors suggest that there might be a slightly higher risk of illness in low income groups than high income groups. Differences in the diets accessible to each of these groups may be a cause of differential incidence of foodborne illness. Research continues to demonstrate that low income groups have access to fewer supermarkets[47] and more independent food markets[51] than their high income counterparts. Certain food environment profiles may play a role in the prevention of foodborne illness in local patrons by providing access to safe food. Results from a recent ecological community survey suggest that produce offered by markets in low socioeconomic status areas contain higher microbial loads than produce offered by high socioeconomic status markets.[82]

Surveys of food safety knowledge and behaviors indicate that while low SES groups report less food safety knowledge than high SES groups, [85, 88] high SES groups may engage in riskier food safety behaviors. For example, those with more income and education were more likely to have a food thermometer but more likely to behave unsafely when handling raw meat compared to those with less than a college degree.[79] Years of education was positively associated with increased understanding of thorough meat cooking, but negatively associated with the practice of consuming thoroughly cooked meat.[85] It is possible that low SES groups over-report socially desirable food safety behaviors, given that they know very little about the reasons for their practices.[88] Indeed, behavioral studies have repeatedly demonstrated that participants often feel the need to over report practices that are deemed to be good.[92-93] In summary, findings on actual/estimated FBI incidence and food safety knowledge and behaviors across SES levels are inconsistent at best. Though the dietary practices of high SES groups might increase risk for FBI, low SES groups may be at greater risk for FBI given both access to a less-favorable food retail profile and a deficit in food safety behaviors and knowledge.

Disparities in FBI risk: foodservice level. Health risk, at the foodservice level, is assessed by inspection of the foodservice facility. Over 85% of State and Territory health departments in the U.S. conduct inspections of foodservices based on guidelines presented in the USDA's Food Code.[96] The purpose of inspections is to minimize risk, defined as the "likelihood that an adverse health effect will occur within a population as a result of a hazard in a food." A critical violation of the food code is defined as an infraction that is "more likely than other violations to contribute to food contamination, illness, or environmental health hazard."[96] Foodservices with relatively few critical infractions may be considered to offer safer food than those with higher rates of violations.

The demographics of the surrounding area may also be associated with violation rate. Pothukuchi et al (2008) examined the relationship between inspection scores and external factors including area poverty level using 2004 inspection data in Detroit. Regression showed that percent of individuals below poverty at the Zip code level significantly affected critical violations reported for an inspection. Specifically, for each additional 10% of persons below poverty, one could expect an increase of 0.6 critical violations.[105]

Detection of environmental gradients. Recently, the ability to pinpoint health outcomes to specific geographic locations has improved greatly. Such geographic analysis is facilitated by Geographic Information Systems (GIS) technology. GIS use is multidisciplinary and has proven useful in mapping community disease risk[107] and food borne illness outbreaks.[108] This technology's utility in food safety research lies in its ability to relate tabular data to geographic entities and perform geospatial analyses. These features can facilitate the detection of environmental gradients.

This research is an effort to examine the association between community socioeconomic level and critical health code violation rate of community food retailers in Philadelphia County, Pennsylvania. GIS technology was utilized to relate socioeconomic data to geographic areas and plot foodservices, and corresponding critical violation rates, within corresponding census tracts.

Though it is unclear whether low income groups truly experience higher rates of foodborne illness than high income groups, it was hypothesized that high poverty areas would display higher numbers of critical health violations per inspection than low poverty tracts. The aim of this study is to apply GIS to a unique area and determine its utility in health inspection research.

Methods

Data acquisition and organization. Demographic data was acquired from the United States Census Bureau.[115] Data was collected at the level of the census tract rather than Zip code to enhance gradient detection. Census Tract is defined as a "small, relatively permanent statistical subdivision of a county…designed to be relatively homogeneous with respect to population characteristics, economic status, and living conditions".[125] The percent of individuals living below the poverty line was used to indicate neighborhood poverty.[47]

Poverty categories were assigned to facilitate comparison of groups. Populated residential census tracts in Philadelphia (N=368) were classified into one of five quintiles, based on the percentage of residents living below poverty. Quintiles included the following poverty ranges: 0%-9.9% (lowest poverty), 10.0-19.3%, 19.8-30.3%, 30.4-44%, and 44.8-78.0% (highest poverty). Average total population is not significantly different between categories ($p = 0.91$). However, poverty categories differed significantly on percent population living at or below poverty and median income ($p<0.01$). Characteristics of each poverty category can be found in Table 7.

Electronic maps containing geographical features of Philadelphia County are publicly available and were obtained from a databank of state information (New Urban Research). Shape files including location, size and shape of census tracts (polygon data), size and shape of county (polygon data), and location, length and cardinal direction of roads and streets (line data) were imported into mapping software (ArcView 9.3, ESRI, Redlands, CA). Maps were projected using a projected coordinate system (NAD 1983 StatePlane Pennsylvania South FIPS 3702).

Foodservice establishment listings. A listing of foodservice establishments and respective health inspection information was compiled from data available on the Philadelphia Department of Public Health website.[116] Listings reflect results from citywide inspections

Table 7. Characteristics of Census Tracts by Poverty Category

	Neighborhood Poverty				
	1 Low (*n*= 85)	**2 Low-medium (*n*= 95)**	**3 Medium (*n*=80)**	**4 High-medium (*n*=67)**	**5 High (*n*= 41)**
Characteristics	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**
Total Pop	3578.1 (2412.7)	4437.8 (2397.1)	4341.4 (2225.2)	4284.1 (2091.1)	3840.5 (2479.1)
Percent Below Poverty*	5.8 (2.9)	14.1 (2.8)	24.9 (3.1)	35.7 (3.9)	52.6 (7.7)
Median Household Income*	$51,989 ($23,037)	$37,339 ($10,604)	$28,218 ($5,251)	$20,862 ($4,037)	$13,929 ($3,446)
Tract Size [square miles]*	0.49 (0.36)	0.32 (0.26)	0.28 (0.15)	0.23 (0.12)	0.25 (0.21)
Foodservices (N)	1498	2893	2413	2237	1818
≥ 2 inspections	1039	2154	1825	1703	1444
< 2 inspections	459	739	588	534	374

No significant difference in population between groups (p = 0.91).
*Percent below poverty, median household income, and tract area significantly different between groups (p<0.001).

between July 2005 and February 2008 and included establishment name, address, general type (e.g. "prepared food take-out" or "restaurant, eat-in"), inspection dates and any observed critical health code violations. Data was transposed from original PDF format to Excel.

Critical health code violations were selected to represent the relative degree of risk conferred by each establishment. According to the FDA, *critical* violations of health code are "more likely than other violations to contribute to food contamination, illness, or environmental health hazard."[96]

Establishments were assigned a designation of *private* or *public* based on type or address. The goal of this analysis was to determine relative risk of foodborne illness conferred by area foodservices to community residents. This assumes food services are publicly accessible and that there is equal potential exposure to all community residents. Thus, food services at private locations were excluded from analysis. This included any locations where patrons must pay for admission (zoo, stadiums, airport), institutions (penal facility, schools),[97] or special membership is required for entry (private club). Therefore, subsequent analyses were performed only on publically accessible establishments.

Mapping. The process of geocoding assigns a longitude and latitude (XY coordinates) to map addresses as points. In order to geocode addresses, an address locator was created within ESRI ArcCatalog, using the network of Philadelphia County's road and streets (Census 2000 TIGER/Line) as reference file. The locator style was *US Streets with Zone*.

Statistical analysis. Data analysis was performed using Statistical Package for the Social Sciences (SPSS, Inc. Chicago, Illinois). The total number of inspections and total number of critical health violations were calculated. This information was used to determine average number of critical health code violations per inspection (CHV rate).

We examined the distribution of CHV rate in the dataset. Histogram of the data revealed a bimodal distribution of CHV rate, dividing the sample in half. Chi Square statistic was utilized to examine whether poverty category affected the distribution of zero- and non-zero CHV rates. Since the data were not normally distributed, and could not be normalized by log transformation (confirmed by one sample Kolmogorov-Smirnov test, (Appendix B: Figure 5) the data were subjected to Kruskal-Wallis non-parametric analysis of variance to evaluate whether CHV rate was significantly different across poverty levels. A p-value of < 0.05 was considered statistically significant in all analyses. Effect size is reported using partial eta-squared value.[117]

Results

Geocoding. Establishments (N= 15,067) were cross referenced using facility name, type and address to check for duplicates. Duplicates were removed (n=399) resulting in 14,668 unique establishments.

The dataset was run through the geocoder's address locator script. Of the unique records, 619 (4.22%) did not geocode on first pass. Original addresses were confirmed and corrected using Google maps. Of unmatched listings, 237 were listed with incorrect zip codes while 272 required minor street address modifications (e.g. typographical or spelling error, cardinal direction missing) while 110 addresses (0.75%) were not able to be located using Google maps and were therefore left uncorrected. Some locations were not able to be geocoded on the basis of street address. Under this circumstance, the addresses were geocoded to the nearest street intersection.[47]

Once corrected, the address file with 14,558 establishments was rerun through the address locator. The address points associated with violations were joined based on spatial location to the census tract level income data. Addresses which were geocoded to tracts with null data for median income were excluded after final geocoding (N=407). After these exclusions, 14,151 unique records remained.

Private establishments (n=3292) were removed from the sample (Appendix B: Table 13). A total of 10,859 public establishments were analyzed (Figure 1). The joined data file was then exported for analysis.

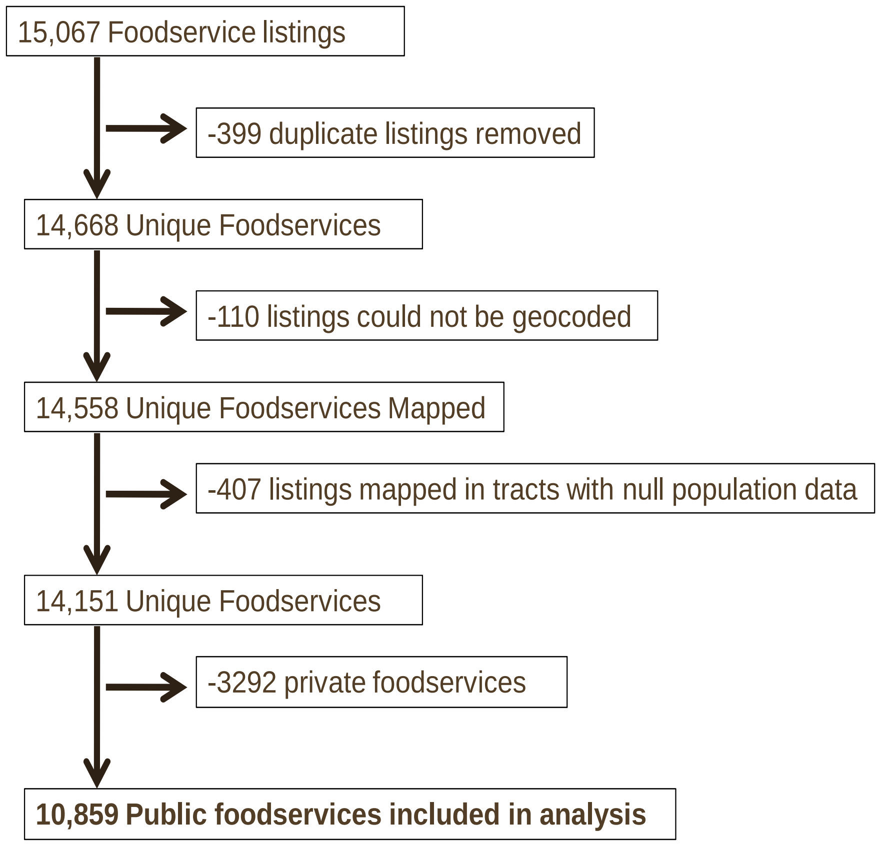

Figure 1. Foodservice Selection Process

CHV presence/absence. Upon visual inspection, the geographic distribution of CHV rates does not appear to meet a pattern (Appendix B: Figure 5). Among the sample of publically accessible establishments (N=10,859), 53.5% had a CHV rate *greater than* zero critical violations per inspection. Chi-square analysis revealed that there was a significant interaction of poverty level on the distribution of establishments with zero CHV rates. The second highest income level displayed the highest percentage of establishments with zero CHV rates (51.7% of establishments within category) whereas the lowest income level displayed the lowest percentage of establishments with zero CHV rates (43.3% of establishments within category) (Table 8).

CHV rate. Average CHV rate and standard error of the mean across all poverty categories was 0.765(0.012) critical violations per inspection. Establishment CHV rates were

Table 8. Distribution of Zero/Non-Zero CHV Establishments, Average CHV and Days between Inspection by Poverty Category

	Neighborhood Poverty				
	1 Low (*n*= 85)	**2 Low-medium (*n*= 95)**	**3 Medium (*n*=80)**	**4 High-medium (*n*=67)**	**5 High (*n*= 41)**
Distribution of Vendors w/Zero CHV rate[a]					
Zero CHV per inspection [n (% of area vendors)]	689 (46%)	*1497 (51.7%)*	1079 (44.7%)	996 (44.5%)	788 (43.3%)
> 0 CHV per inspection [n (% of area vendors)]	809 (54.0%)	*1396 (48.3%)*	1334 (55.3%)	1241 (55.5%)	1030 (56.7%)
Critical Healthcode Violations[b]					
Total vendors (N)	1498	2893	2413	2237	1818
Average CHV per inspection [Mean(SE)]	0.931 (0.0397)**	0.726 (0.0249)*	0.747 (0.0235)*	0.724 (0.0228)*	0.766 (0.0254)*
Days between Inspections[c]					
Total vendors (N)	1039	2154	1825	1703	1444
Average days between inspection [Mean(SD)]	241.2 (155.8)**	247.6 (145.2)**	207.2 (143.9)*	204.1 (136.2)*	214.4 (140.5)*

a. χ^2= 46.028, df = 4, p = 0.001
b. All means, with the exception of Poverty Category 1 are similar (Kruskal Wallis χ^2= 40.387, df = 4, p < 0.001; Games-Howell multiple comparisons p>0.05 for all tests except where noted**p<0.005).
c. Means of Poverty Category 1 & 2 are similar , Means of Poverty Categories 3,4&5 are similar. (Kruskal Wallis χ^2= 143.271, df = 4, p < 0.001; Games-Howell multiple comparisons p>0.05 for test with similar notation. Differences where noted, significant at p<0.005)

analyzed via Kruskal-Wallis nonparametric analysis of variance (N=10,859) and revealed a significant difference in CHV rate distribution across poverty quintiles ($p < 0.001$). The highest CHV rate, as displayed by the highest mean rank, was found in poverty category 1 (high income).

Post-hoc pair-wise multiple comparisons were conducted using the Games-Howell post hoc test which is appropriate for handling unequal variances[118] and unequal sample sizes.[119-120] Presence of unequal variances was confirmed by Levine's test ($p <0.001$) and further supported use of Games-Howell procedure. Games–Howell post hoc tests revealed that CHV rate in poverty category 1 (high income) (mean = 0.93 CHV per inspection) was significantly higher than any other group ($p < 0.005$ for all tests). There were no significant differences between CHV rates differences between poverty categories 2, 3, 4, and 5 (Table 8). This was a small difference as 3% of the variance is accounted for in the difference (Partial Eta Squared = .003).

Inspection frequency. Since CHV rate may be related to inspection frequency, we also calculated the average number of days that elapse between inspections. Inspection dates were used to calculate the average number of days between inspections for each establishment. Due to the nature of the variable, only establishments with 2 or more inspections were included in analyses pertaining to average days between inspections.[99] The number of establishments with only one or two or more inspections across poverty quintiles can be found in Table 7.

The data of average days between inspection for publically accessibly establishments with 2 or more inspections (N=8,165) (Table 8) was not normally distributed and, again, could not be normalized by transformation (Appendix B: Figure 7). The mean and standard deviation for number of days between inspections for all public establishments with 2 or more inspections was 222.8 $\pm$ 144.8 days. Analysis using Kruskal-Wallis revealed a significant difference in number of days between inspections across poverty quintiles ($p < 0.001$). The greatest number of days between inspections, as displayed by the highest mean rank, was found in poverty category 2 (2^{nd} highest income level).

Post-hoc pair-wise multiple comparisons were again conducted using the Games-Howell post hoc test. Levine's test ($p <0.001$) confirmed presence of unequal variances. Games–Howell post hoc tests revealed that number of days between inspections was significantly greater in poverty categories 1 and 2 (high income) (241.2 days and 247.6 days, respectively) than in any other group ($p < 0.005$ for all tests). There were no significant differences in days between inspections between poverty categories 1 and 2 or between categories 3, 4, and 5 (Table 8). The effect size corresponding to the difference was small (Partial Eta Squared = .016).

We tested the strength of the association between poverty and CHV rate and inspection frequency. To test if establishment CHV rate was related to the percent of population below poverty, we subjected the data to a nonparametric correlation procedure (N=10,859). There was a significant but small positive correlation between percent poverty and CHV rate (Spearman's rho = 0.024; $p = 0.013$). To test if the number of days between inspections (among establishments with ≥ 2 inspections; N=8,165) was related to the percent of population below poverty, we again subjected the data to a nonparametric correlation procedure. There was a significant but small negative correlation between percent poverty and number of days between inspections (Spearman's rho = -0.097; $p = 0.013$). To test the effect of poverty on CHV rate in the absence of the effect from inspection frequency, the data (N=8,165) were subjected to a first-order partial correlation. The test revealed a small but significant negative correlation ($r = -0.071$; $p<0.001$) indicating that lower poverty rates are associated with lower rates of CHV, irrespective of inspection frequency.

Discussion

Assessment of critical healthcode violations is a way of quantifying relative risk of food borne illness conferred by a foodservice.[96] The results of the current analysis suggest that foodservice establishments in high income areas confer greater health risk than establishments in lower income areas. This finding is not in accordance with available literature.[105] Not only did establishments in areas in the highest income category have significantly more critical healthcode violations per inspection than any other group, but establishments in the two highest income areas were inspected less often than establishments in lower income areas, indicating that CHV rate may not be a function of inspection frequency, a finding that is in accordance with other studies.[99]

Upon initial inspection of distribution of establishments with zero versus non zero CHV rates, it appeared that the two highest income categories had the greatest percentage of establishments with zero CHV rates. Upon further inspection, however, establishment CHV rate (including zero and non-zero rates) was found to be significantly higher in the highest income area. The relatively small effect size indicates that the income level of an area seems to be a factor in establishment CHV rate, but not likely the only or dominant factor.

Income is typically tightly correlated with percent Caucasian in an area. Though the investigation of race/ethnicity effects on CHV is outside the original aim of this research, a post-hoc Poisson regression was run to model the effects of, and interaction between, poverty category and percent Caucasian population (percentage category tertiles) on CHV rate counts when controlling days between inspection. Only those foodservices (N=3926) with two or more inspections were included and the model did not include foodservices with a zero CHV rate (to eliminate overdispersion). The Poisson regression model predicting CHV rate from percent Caucasian population was statistically significant with Wald chi-square = 8.321, df=2 yielding p-value <.0001. The predictor, poverty category, was not significant (Wald chi-square = 9.213, df=4, p = 0.056) and was dropped from the model. For these data, the highest Caucasian group (73.46-100% Caucasian) was predicted to have 1.30 CHV rate, while the middle Caucasian group (17.4-73.45% Caucasian) was predicted to have 1.17 CHV rate, while days between inspection was held constant. Given these findings, race and ethnicity may not effect CHV rate in the direction previously though.[105]

If an establishment is found to be noncompliant with regards to sanitation code, it is typical that the establishment may receive a follow up inspection within a specified period after the initial inspection. This is in accordance with our finding that there is a strong, statistically significant negative correlation between CHV rate and days between inspections. However, when the number of days between inspections in each poverty category were analyzed, we found that the establishments in low income areas had the fewest days between inspection, meaning that inspectors were returning to these (low CHV rate) establishments more often than those in the high income areas (with high CHV rates).

In Philadelphia, foodservices are required to receive an inspection at least every 12 months (P.Raval-Nelson, Philadelphia Department of Public Health, personal communication, December 4, 2008). Inspections exceeding this frequency may be follow-ups to annual inspections or in response to a complaint. Though we observed both a negative relationship between CHV rate and poverty, indicating that lower income areas display lower foodservice critical violation rates, and a negative relationship between days between inspection and CHV rate indicating an association between more frequent inspections and less frequent violations, we observed a negative relationship between poverty and days between inspections indicating increased inspection frequency is associated with lower area income. It is possible that inspection frequency influenced CHV rate whether positively or negatively. More frequent inspections may cause foodservice workers to be more vigilant of violations, but more frequent inspections give the inspectors additional opportunities to cite violations. However, after controlling for number of days between inspections, poverty was still negatively correlated to average CHV, albeit very slightly. This suggests that the higher CHV rate in the high income category is not a result of being inspected more often. It is important to note, though, that significance in this relationship may be an artifact of the rather large sample size. Anecdotally, it may be the case that health inspectors feel compelled to frequent establishments in low income areas because the facilities are generally not as new and often in states of disrepair. Jones et al (2004) noted that Tennessee's inspection protocol, modeled after the Food Code, required inspectors to include factors having little bearing on illness prevention in observations including the inspection of non-food-contact surfaces.[97] The authors note that this may impact the inspectors' general impression of the establishment's operation. Though infraction type was not analyzed in the current study, the violations tracked in the dataset were all considered to be critical violations by the Philadelphia Department of Public Health, covering the topics of sanitation, time/temperature abuse, contamination, employee hygiene and presence of food safety certificate.

It is possible that more frequent inspections perpetuate a cycle of fewer violations in high poverty areas. However, our finding that controlling for inspection frequency does not change the direction of the (negative) relationship between poverty and CHV rate is consistent with the literature in general suggesting that there is no association between increased inspection frequency and reduction in violations.[97, 99, 101] While reducing inspection frequency has been shown to result in a decline in sanitation compliance,[103-104] increasing inspection frequency does not improve sanitation compliance.[100, 102] Newbold et al (2008) reported that a pre-intervention survey administered to 21 inspectors revealed the majority of inspectors (76%) initially "felt that increasing the number of routine inspections would result in fewer violations".[99] This may further explain the bias toward more frequent inspections in lower income, older establishments. Less compliant establishments should be inspected more frequently.[99, 126] This should be based on empirical data and not based on impressions. In our study, CHV rate was significantly negatively correlated to days between inspection (frequency) among publically accessible establishments inspected 2 or more times (Spearman's rho = -0.502; $p < 0.001$). As indicated by the fewer days between inspections, inspectors are making a disproportionate number of visits to high poverty areas considering relative rate of CHV.

There are a number of factors which could influence the reported CHV rate that could not be assessed and thus present a few caveats to our study results. According to the 2005 Food Code, establishment inspection rate should be based in part on the establishment's own risk category. In the current study, inspection rate was significantly lower (more time between inspections) in the two highest income groups than other groups. Number of inspections per facility per year across poverty levels may vary because number of high risk food establishments varies across poverty categories. In our study, it is difficult to conclusively assign risk category to vendors. Future health inspection reports should include assignment of risk categorization for each food establishment, based on the amount of food storage and raw food handling.[96] It is recommended that high risk establishments undergo inspection more often than low risk establishments. For example, the 2005 Food Code puts forth the following guidelines: Risk category 1 – Convenience store operations, hot dog carts, and coffee shops; Category 2 – retail food stores, quick service operations (limited menu); Category 3 – Full service restaurants (extensive menu and handling of raw ingredients); Category 4 – establishments serving highly susceptible populations or conducting specialized processes (smoking/curing). Assignment of risk categorization would provide justification for variation in inspection rates. This system is utilized in a number of localities, including Ontario Canada.[99]

The physical size of establishments may also affect compliance rates, though the exact direction of the relationship is unclear. Buchholz et al (2002) found that medium and large size establishments were, respectively, 2.8 and 4.6 times as likely to receive consumer-complaints and subsequent sanitation inspections.[126] However, Yapp and Fairman (2006) report that due to reduced availably of resources, inherent mistrust of regulations/inspectors and a general lack of knowledge, small and medium food operations in the UK often present with poor sanitation compliance.[106] In our study, analysis was limited to the data available on the Health Department's website and did not include information pertaining to physical size of establishment. Future inspections might be well served to denote general establishment size based on total square footage to facilitate analysis of sanitation compliance based on establishment size.

We are unable to differentiate between inspection types such as routine inspections, re-inspections, and complaint follow-ups. It is important to consider, though, that "restaurant inspections conducted specifically in response to customer complaints may not identify critical violations any more than inspections conducted at restaurants free from such complaints."[127]

The present study assumes training and bias is equal among inspectors. According to the 2005 Food Code, it is recommended that Inspector training should involve all of the following components: classroom training, field training and experience, standardization and continuing education.[96] Though Jones et al (2004) concluded that inspections are "easily influenced by subjective interpretation" and difficult to standardize,[97] it is possible that if inspections that were the work of inspectors with the least amount of training were removed from the dataset, there may be less variation in the results. Furthermore, individual characteristics of inspectors may impact reported violation rate. Pothukuchi et al (2008) examined the relationship between inspection scores and the gender of inspector. Regressions showed that the inspector's gender significantly affected critical violations reported for an inspection to the extent that female inspectors were found to report about one more critical violation than males.[105] In the current study, it is possible that, due to safety concerns in low income areas, female inspectors may have been generally assigned to high income areas. This scenario may be a possible explanation for the inflated CHV rate found in the highest income group.

Finally, although the highest income group was found to have more CHVs per inspection, it is difficult to interpret the practical meaning of such findings. A number of studies have investigated the link between healthcode violations and incidence of foodborne illness with mixed results. Jones et al (2004) found that inspection scores of restaurants associated with FBI outbreaks were not significantly different from other restaurants.[97] Similarly, in a study of 1995 FBI rates in Miami-Dade County, Florida, Cruz et al (2001) found that violation rates were not directly linked to incidence of foodborne illness.[128] In contrast, Bader et al (1978) found that a greater percentage of foodborne illness reports were associated with establishments with high inspection frequency rates.[103] Mathias et al (1994) found that incidence of FBI was associated with the frequency of citations.[104] Finally, in a study by Irwin et al (1989), completed in Seatle-King County, Washington in 1987 restaurants with poor sanitation compliance were more likely to produce foodborne illness.[129] Thus, interpretation of degree of increased risk imposed by higher CHV rates in high income area establishments is difficult.

In summary, foodservice establishments in lower income communities in Philadelphia undergo significantly more inspections but generate significantly fewer critical health violations per inspection. The pressure of increased inspection frequency was thought to influence the observed CHV rate, however, the relationship between low income and low CHV rate still persists when the number of days between inspections is held constant. Using CHV rate as a proxy for access to safe food and subsequent rates of foodborne illness in the community, we found that high income communities have reduced access to safe food and may, therefore, be predisposed to increased rates of illness compared to low income groups. The health of community residents would be best served if resources (both funding and time) were focused on non compliant establishments wherever they may be.

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APPENDIX A: FOOD ACCESS SUPPLEMENT

Appendix A: Table 9. North American Industry Classification System[130]: Codes of Interest

Sector	Type	Subtype of Interest	Subtype Description	Classification for Analysis
44-45 Retail Trade	4451 Grocery Stores	445110 Supermarkets and Other Grocery (except Convenience) Stores	"Retail a general line of food (canned/frozen foods, fresh fruits and vegetables; and fresh and prepared meats, fish, and poultry). Delicatessens retailing general food line included."	Grocery
44-45 Retail Trade	4451 Grocery Stores	445120 Convenience Stores	"Retails a limited line of goods (generally, milk, bread, soda, and snacks). Includes food marts with out fuel pumps."	Convenience
44-45 Retail Trade	4452 Specialty Food Stores	445210 Meat market	"Establishments primarily engaged in retailing fresh, frozen, or cured meats and poultry. Delicatessen-type establishments primarily engaged in retailing fresh meat are included in this industry."	Meat&Fish Market
44-45 Retail Trade	4452 Specialty Food Stores	445220 Fish & Seafood market	"Establishments primarily engaged in retailing fresh, frozen, or cured fish and seafood products."	Meat & Fish Market
44-45Retail Trade	4452 Specialty Food Stores	445230 Fruit and Vegetable Markets	establishments primarily engaged in retailing fresh fruits and vegetables.	Produce Market
44-45Retail Trade	4452 Specialty Food Stores	445291 Baked Goods stores	Establishments primarily engaged in retailing baked goods not for immediate consumption and not made on the premises.	Fast-food/take-out *Only "Donut" establishments included in analysis
44-45Retail Trade	4471 Gasoline Stations	447110 Gas station convenience	Establishments engaged in retailing automotive fuels (e.g., diesel fuel, gasohol, gasoline) in combination	Convenience

			with convenience store or food mart items. These establishments can either be in a convenience store (i.e., food mart) setting or a gasoline station setting. These establishments may also provide automotive repair services.	
72 Accommodation and Food Services	7222 Limited service eating places	722211 Limited service restaurants	Food services (except snack and nonalcoholic beverage bars) where patrons generally order or select items and pay before eating. Food and drink may be consumed on premises, taken out, or delivered to customers' location. Some establishments in this industry may provide these food services in combination with selling alcoholic beverages.	Fast-food/take-out
72 Accommodation and Food Services	722 Full service eating places	722110 Full service restaurants	Foodservices where patrons order and are served while seated (i.e., waiter/waitress service) and pay after eating. Establishments that provide this type of food service to patrons with any combination of other services, such as take-out services, are classified in this industry.	Full-service

*From “Baked Goods Stores” only “Donut” and chain bakeries were considered as ‘take out’ and included in “limited service restaurants”

Appendix A: Table 10. Keywords Utilized in Classification of PDPH Database

Category (Data Code)	**Keywords**
Convenience (1)	7-11, 99 cent, Convenient, Convenience, Corner (if not previously “prepared food take out” or “restaurant”), Corner store, “Deli & Mini Market”, Discount, Dollar, Express/Xpress food market, Food cart, Food corner, Gas/petro/fuel station, General, General store, Kmart, liquidators, Mini mart, Mini market, One-stop, Quick/quik/kwik, Stop (if previously convenience or grocer), Target, Valu/e, Variety, Walmart, Wawa, [recognizable regional drugstore brand]
Grocery (2)	Bodega, Deli, Farm, Food Center, Food Mart, Food Market, “Fish/meat+fruit/vegetable”, Grocer, Groceries, Grocery, Market,Mart, Mkt, Tienda/tiendita
Supermarket (3)	Super Market, Supercenter, Supermarket, [recognizable regional/national brand]
Restaurant, Eat In (5)	Diner, bistro, cafes (independent, ie <2 locations), cuisine, grill, luncheonette, pub, “restaurant & bar/lounge”, “restaurant [name]”, chain restaurants (e.g., IHOP, Applebee’s), ristorante, saloon, steakhouse, sushi, tavern
Prepared food/take-out (6)	Bakeries (chain), bagel(s), BBQ/jerk, burger, cafes (chain; fast & express), cereal, chicken, Chinese (fast/express) coffee/latte/java/espresso, “deli & restaurant”, dog(s)/hot dog(s)/wiener(s)/franks, donut(s), food court, fried/fry/fries, “grill & deli”, hoagie, juice/smoothie, lunch take out, meat/cold cut, Mexican (fast & express), pizza (not including Pizza Hut), pretzels, rib(s), salad, sandwich, seafood (fast & express), snack, soup, steak(s)/cheese steak(s), subs, taco, take-out/take out, tea, to-go, wings, wok, wrap. *Listings originally classified as “restaurants” containing the keywords “fast” or “express” *Listings originally classified as “prepared food/take out” containing the keyword “corner” but not “store” *Listings originally classified as “restaurant, eat in” containing the keyword “corner” *Listings originally classified as either “prepared food/take out” or “restaurant, eat in” containing the keyword “stop”
Meat/fish market (8)	Butcher, fish, meat(s), poultry, prime *Listings originally classified as “general convenience” or “grocery market” containing the keywords “seafood”, “hallal” or “kosher”
Produce Market (9)	Fruit, Produce, Vegetable
Other	Antique(s), auto/car maintenance, bakery/panederia/patisserie/pastry, beauty , bed, *alcohol related* (beer, beverage, bottle, brew, distributor, drink, liquor, six pack, vineyard, wine), billiard(s), bingo, boat, body, books,

	candy/candies, carwash, caterer, chocolate, cigar/cigarettes/tobacco/smoke, check, cheese, circuit, Claire's, clean, coat, coconuts, community center, condom, conference, cookware, crabtree, crafts, culture, cyber/internet, dairy, drugstore(s)/apothecary/pharma (independent), eggs, electronics fashion/clothing, florists/flowers, Forman Mills, fountain, game, gift, hair, hardware, home goods, imports, jewel(s)/jewelry, laundry/suds/sewing, lobby, lotto, lounge, natural, nursery, nutrition, health center, health food store, nuts, office, office supplies, party, party supply, pet(s), pet supply, prescription, puppy, record(s), religious (pray, church, Catholic, rentals, spice/herb, sport(s), stationary, studio, style, soup kitchen, sweet/dolce, tanning, thrift, toys, travel, union, vending machines, video, vitamin, water ice/gelato/custard/ice cream, weight loss *Listings containing the keyword "news" or "newsstand" that were not originally classified as "mobile food vendors" *Listings containing the keyword "bar" if name precedes word "bar" (including sports bars, club(s) and night club(s) *Listings originally classified as "other" not receiving secondary classification
Private	Activity/group club or hall, airport addresses, bowl(ing)/lanes, cafeteria, cinema/theater, club, correctional facilities, fitness/gym, museums, skate, stadiums (Wachovia Spectrum, Wachovia Center, Lincoln Financial Field, Citizens Bank Park, Liacouras Center, Franklin Field), university (including dining hall), wholesale, zoo
Mobile food vendor (10)	Original classification used

NOTES:Word order important (bakery & café → other; café & bakery →restaurant, eat-in). Unidentified establishments include those with keywords like "kitchen", "place", "house", "store", "restaurant" "buffet" "breakfast".

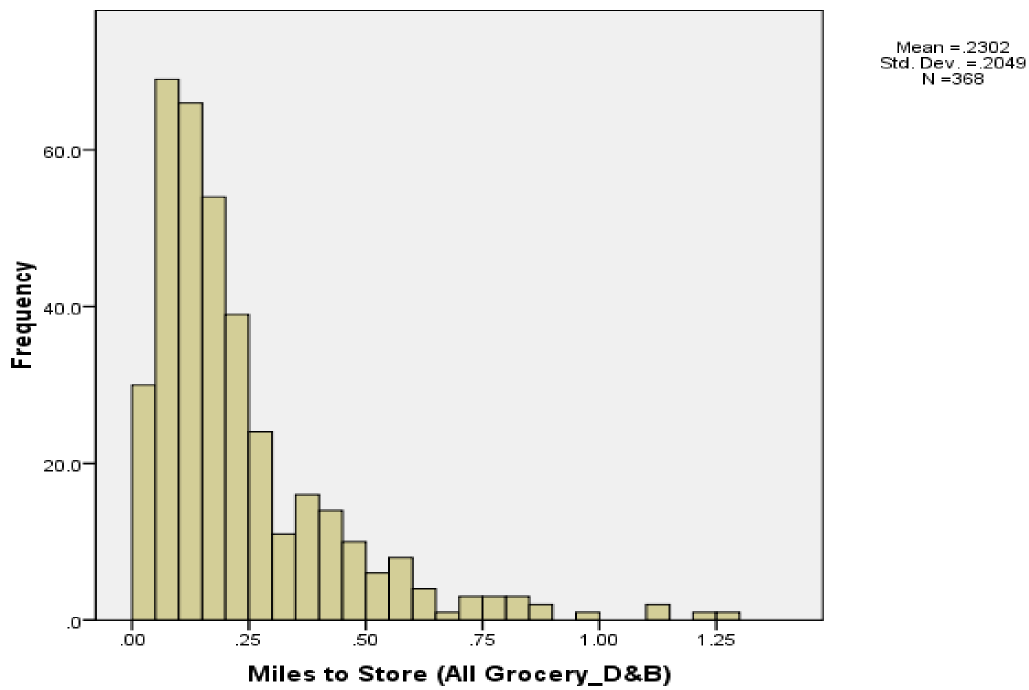
Appendix A: Table 11. Distribution of Unclassified Vendors by Poverty Category (PDPH)

	Neighborhood Poverty				
	1 Low (*n*= 85)	**2 Low-medium (*n*= 95)**	**3 Medium (*n*=80)**	**4 High-medium (*n*=67)**	**5 High (*n*= 41)**
Store Type	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**
Unclassified	394 (26.3%)	***796 (27.5%)***	***577 (23.9%)***	566 (25.3%)	456 (25.1%)
Classifiied	1104 (73.7%)	***2087 (72.5%)***	***1836 (76.1%)***	1671 (74.7%)	1362 (74.9%)

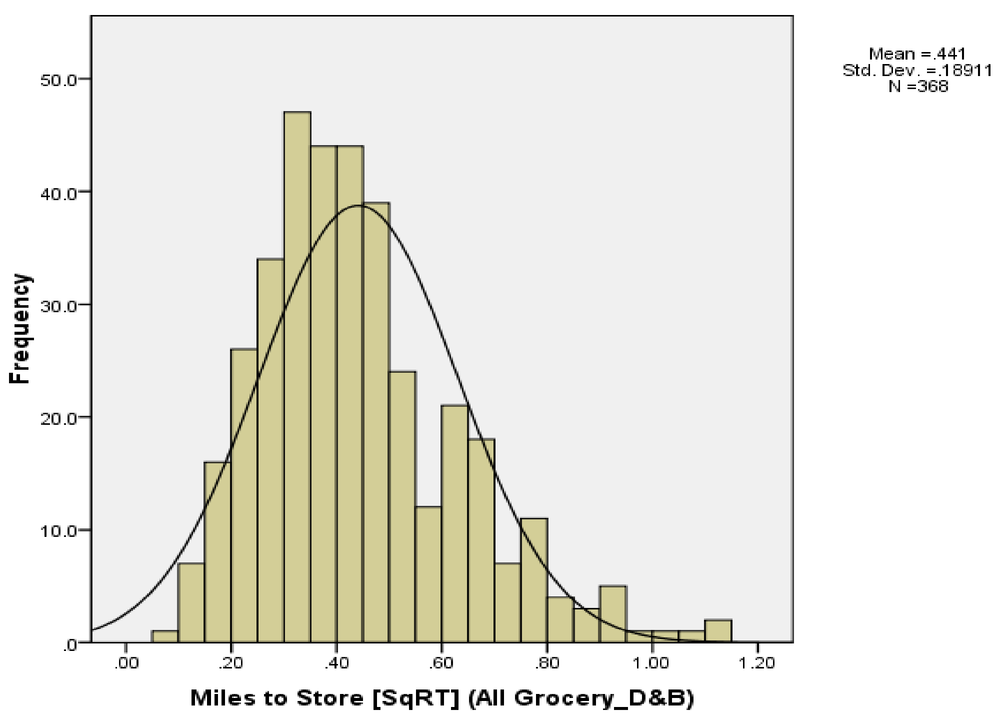
*χ^2= 9.85, df = 4, p = 0.043

Appendix A: Table 12. Common Unclassified Vendor Types (PDPH)

Category Unable to be Classified (frequency $\geq$ 5 listings)	**Number of Vendors**	**Percent of Total Unclassified**
Lacking keyword in vendor name	1566	56.2%
“Restaurant”	622	22.3%
“House”	114	4.1%
“Place”	74	2.7%
“Garden”	65	2.3%
“Sea/Seafood”	65	2.3%
“Kitchen”	49	1.8%
“Inn”	48	1.7%
“Food(s)”	45	1.6%
“Store”	24	0.9%
“Breakfast/Lunch”	24	0.9%
“Taste”	23	0.8%
“Palace”	19	0.7%
“Buffet”	14	0.5%
“Room”	12	0.4%
“King”	12	0.4%
“City”	8	0.3%
“Eatery”	5	0.2%
Total	2789	

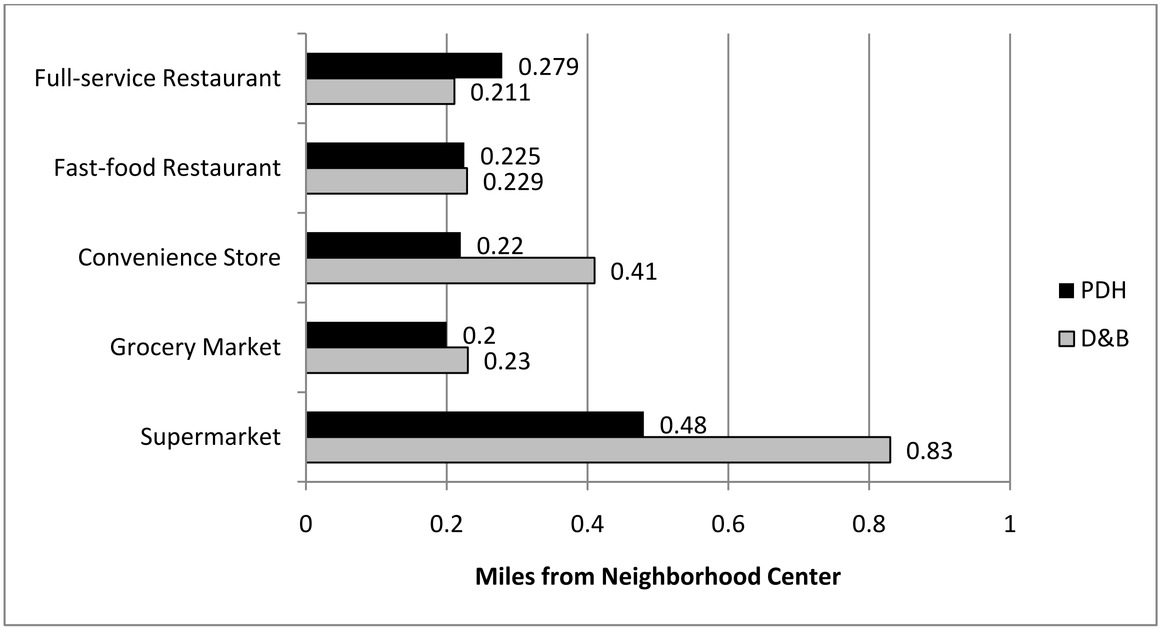


SE = 0.011; Skewness = 2.03 (0.127); Kurtosis =5.23 (0.254); Kolmogorov-Smirnov Z = 3.2 [p<0.001]



SE = 0.0986; Skewness = 0.893 (0.127); Kurtosis =0.822 (0.254), Kolmogorov-Smirnov Z = 1.74 [p = 0.005].

Appendix A: Figure 2. Attempted Normalization of Distance Data (e.g., D&B All Grocery)



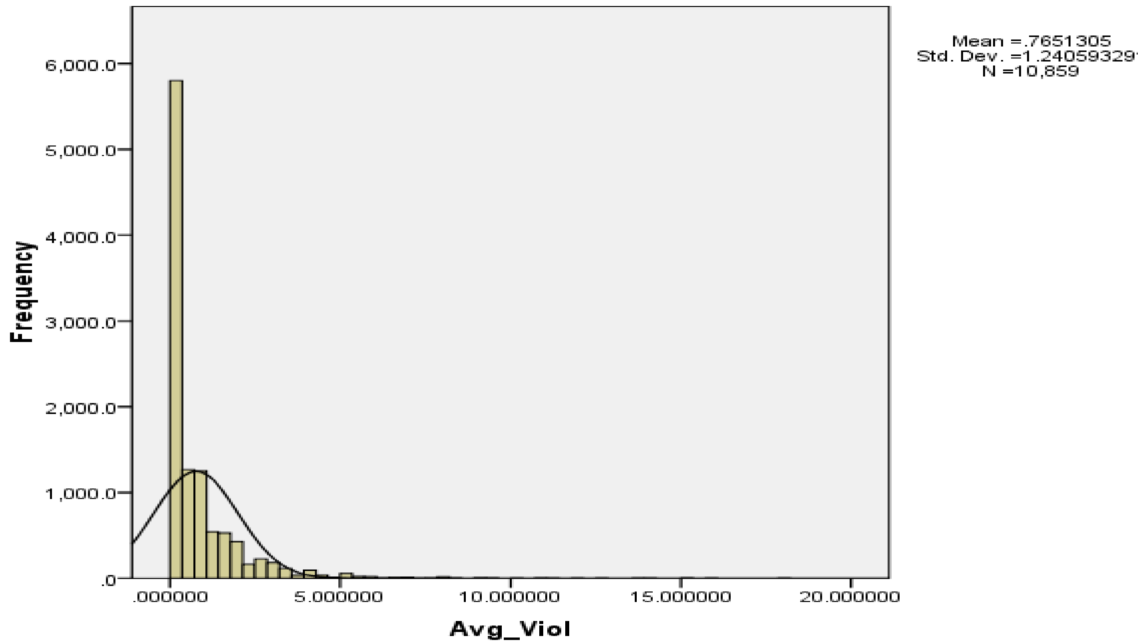
Appendix A: Figure 3. Distances to Establishments of Interest across All Tracts, by Dataset

APPENDIX B: FOOD SAFETY SUPPLEMENT

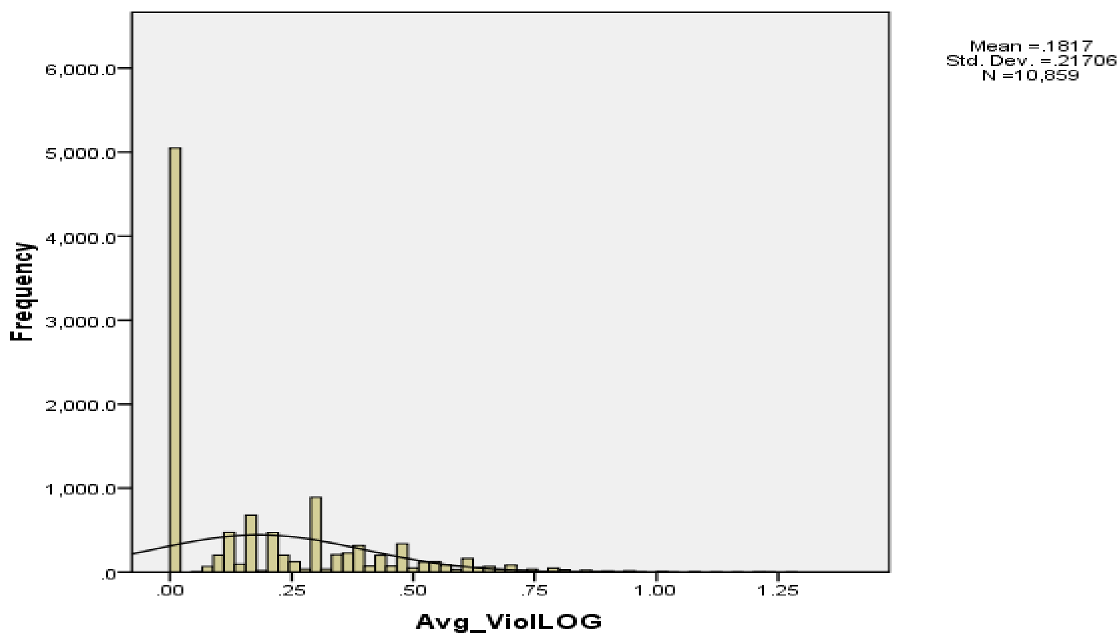
Appendix B: Table 13. Distribution of Public/Private by Poverty Category

	Neighborhood Poverty				
	1 Low (*n*= 85)	2 Low-medium (*n*= 95)	3 Medium (*n*=80)	4 High-medium (*n*=67)	5 High (*n*= 41)
Characteristics	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**	**Number of vendors (% of area vendors)**
Private foodservices	504 (25.2%)	750 (20.6%)	872 (26.5%)	713 (24.2%)	453 (19.9%)
Public foodservices	1498 (74.8%)	2893(79.4%)	2413 (73.5%)	2237 (75.8%)	1818 (80.1%)

N=14,151; 23.3% Private
*χ^2= 53.873, df = 4, $p < 0.001$

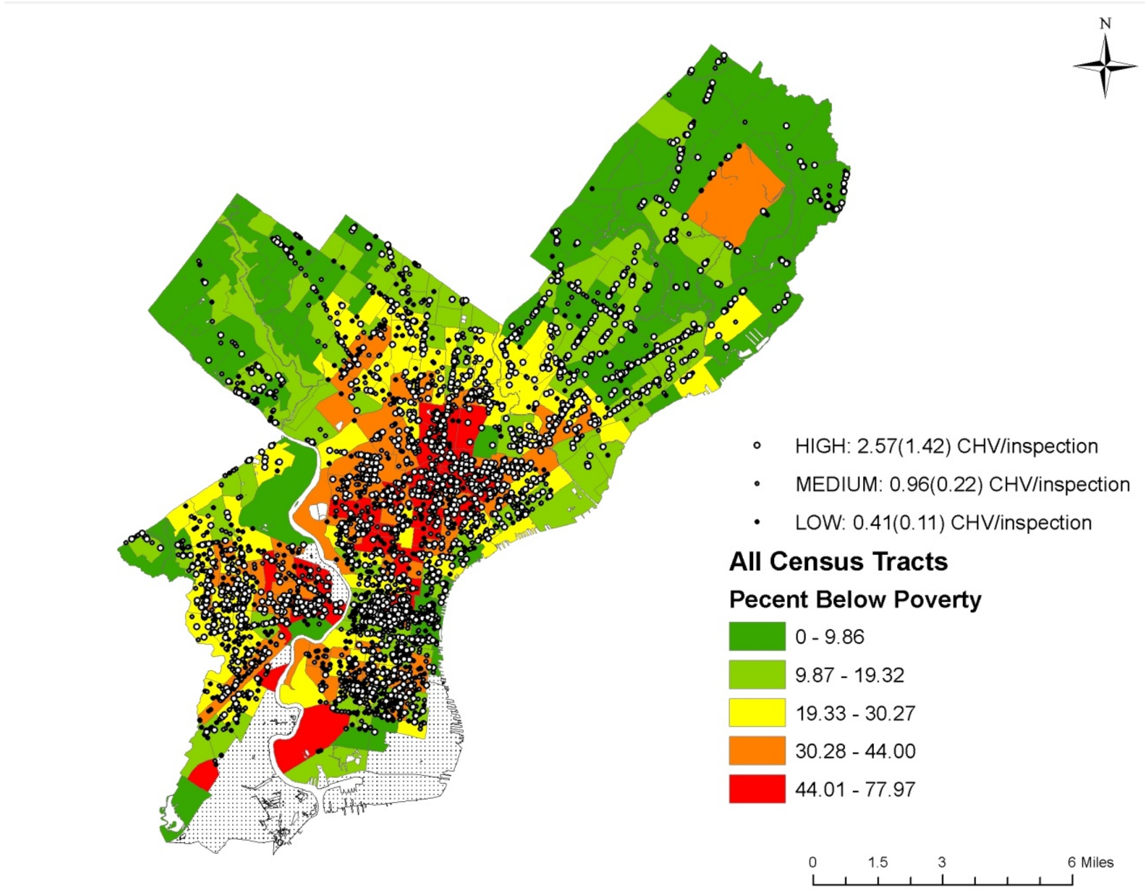


SE = 0.012; Skewness = 3.574 (0.024); Kurtosis = 22.856 (0.047); Kolmogorov-Smirnov Z = 28.0 [p<0.001]

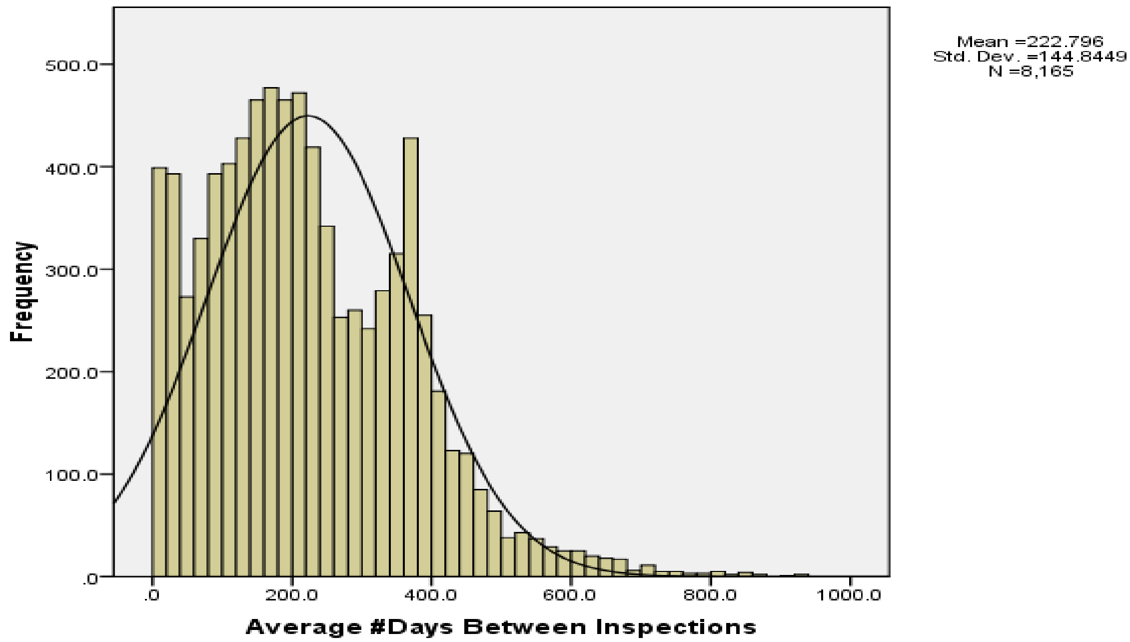


SE = 0.002; Skewness = 1.123 (0.024); Kurtosis = 0.768 (0.047); Kolmogorov-Smirnov Z = 27.48 [p<0.001]

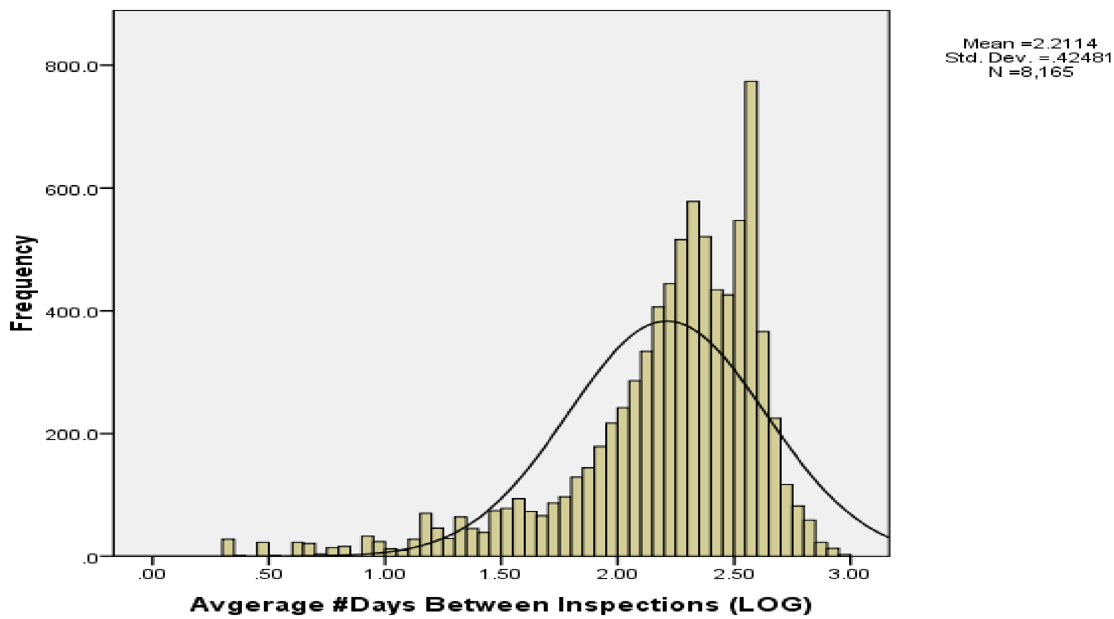
Appendix B: Figure 4. Attempted Normalization of CHV Data



Appendix B: Figure 5. Geographic Distribution of CHV Rates in Philadelphia



SE = 1.603; Skewness = 0.743 (0.027); Kurtosis =0.627 (0.054); Kolmogorov-Smirnov Z = 5.7 [p<0.001]



SE = 0.0047; Skewness = -1.576 (0.027); Kurtosis = 3.075 (0.054); Kolmogorov-Smirnov Z = 10.991 [p<0.001]

Appendix B: Figure 6. Attempted Normaliztion of Inspection Frequency Data